

The Pursuit of Profit or Prestige: What the Diffusion of MOOCs Can Tell Us about
Disruptive Innovation in US Higher Education

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ABSTRACT

THE PURSUIT OF PROFIT OR PRESTIGE: WHAT THE DIFFUSION OF MOOCs CAN TELL US ABOUT DISRUPTIVE INNOVATION IN U.S. HIGHER EDUCATION

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Disruptive innovations are used to lower costs and augment access to high-quality, affordable higher education, but little systematic research is available on the topic. Higher education institutions use disruptive innovations to save students time and money. To understand the process of disruptive innovation, I investigated the rapid diffusion of Massive Open Online Courses (MOOCs), which are free or low-cost college courses available online. Specifically, I examined the drivers of disruptive innovation over time and by institution type, and augmented the existing theory on the diffusion of disruptive innovation in higher education. The key for this systematic study was to have a dataset that encompassed a large sample of adopters and non-adopters. I constructed a new dataset merging 4 years of IPEDS data with MOOC data ($n = 1,470$). Analytically, I used competing drivers of institutional change, specifically prestige-seeking versus economic competition, to investigate rate and drivers of adoption, how drivers varied over time, and which institutions were most and least likely to innovate. I employed time-series inferential statistics, specifically discrete time hazard modeling (DTHM), and latent class analysis (LCA), as well as descriptive statistics.

Three research questions guided this dissertation.

1. When is MOOC adoption most likely? How does prestige-seeking behavior compared to economic competition influence the adoption of MOOCs?
2. Does partnership with a for-profit versus nonprofit provider differ by prestige-seeking behavior or economic competition? Do these partnerships change over time?
3. To what extent does a typology of institutional innovators based on prestige-seeking behavior and economic competition exist? To what extent does this typology of innovators relate to MOOC adoption? How does the adoption of innovation by institutional subgroup vary over time?

The findings suggested that rate of adoption, at its height, was a little over 3% in academic year 2013, 2 years after the launch of MOOCs. Both prestige-seeking behavior and economic competition were important predictors of innovation, although institutions most likely to innovate were very prestigious and strategic about the markets they chose for competition. Specifically, the most likely adopters of disruptive innovation were highly competitive in distance education and in pursuing private grants and contracts from industry, but often did not cut costs (e.g., replacing full-time faculty with adjuncts or expanding managerial capacity) to streamline affairs on campus or manage market expansion. By contrast, institutions that did not innovate often exhibited the opposite characteristics. Finally, because the first two results suggested different adopters, I found five different types of institutional innovators (Accelerators, Wealth Managers, Pragmatists, Opportunists, and Laggards). Approximately 15% of colleges were Accelerators (primed to be disruptive innovators), while the rest were characterized by limited motivate to change or limited institutional capacity to innovate.

Table of Contents

Table of Contents	i
List of Tables	iii
Acknowledgements	v
Dedication	vi
Chapter 1: Introduction	1
Research Questions	7
Theoretical Approach and Conceptual Framework	8
Empirical Approach	11
Analytic Approach	11
Chapter Overview	13
Operational Definitions	13
Chapter 2: Background and Conceptual Framework	15
Changing Political Economy of Higher Education	15
Higher Education Economic Constraints	18
A Federal Higher Education Innovation Agenda and Economic Competition	19
MOOC Antecedents	21
Emergence of MOOCs	30
Differences Between MOOCs and OCW/OER	32
Institutional Motives and Goals for MOOCs	33
The Politics of MOOCs and Open Online Education	36
Costs and Associated Problems of Disrupting Higher Education	38
In Review	41
Theoretical Framework	42
Chapter 3: Methods	52
Population and Data Collection	52
Sample	54
Measures	56
Dependent Variables	56
Independent Variables	59
Empirical Approach	71
Chapter 4: Results	91
Section 1. The Determinants of MOOC Adoption	94
Section 2: The Motives of MOOC Adopters	108
Section 3: Latent Class Analysis of Institutional Innovators	119
Chapter 5: Discussion & Conclusion	134
Review of Study	134
Review of Findings	138
Policy Implications	148
Limitations of the Present Study and Areas for Future Research	152
References	157

Appendix A: Discrete Time Hazard Model Code.....	171
Appendix B: Subgroup Analysis of Mechanisms by Provider Code.....	176
Appendix C: Mplus Code for LCA Analysis.....	182
Appendix D: Missing Data Analysis	182

List of Tables

Table

Table 1. Adoption by For-profit and Nonprofit Providers.....	58
Table 2. Indicators of Prestige	62
Table 3. Indicators of Economic Competition	66
Table 4. Indicators of Institutional Capacity.....	70
Table 5. Emergence of Providers Over Time by Number of Partnerships	80
Table 6. Descriptive Variables and Frequencies.....	97
Table 7. Life Table for the Event Histories for the Adoption of MOOCs.....	99
Table 8. Results of Fitting Five Discrete Time Hazard Models to Year of First Adoption.....	104
Table 9. Associations Between Providers and Mechanisms of Change	112
Table 10. Adopter Characteristics Over Time	114
Table 11. Characteristics of First-time Adopters by Provider Type for AY 2011-AY 2014	115
Table 12. LCA Results and Fit Statistics for Types of Innovators	124
Table 13. Classification Probabilities for the Most Likely Class Membership	125
Table 14. Probabilities of Mechanisms of Innovation by Group.....	126
Table 15. Probabilities of Adopting a MOOC by Group.....	131
Table 16. Statistical Significance Between Groups.....	132
Table D1. Missing Data for Starting Sample Pre-listwise Deletion	182
Table D2. Comparing Determinants by Missing (deleted) Cases.....	182

List of Figures

Figure

Figure 1. Structural and conceptual equation model for LCA of MOOC adoption	85
Figure 2. Estimated hazard probability	100
Figure 3. Estimated survival probability	100
Figure 4. Differences in characteristics of first-time adopters by provider type over time	117
Figure 5. Statistical indicator plot	127
Figure 6. MOOC adoption by group from AY 2011-12 to AY 2014-15	133

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Dedication

For Ben. I did it!

Chapter 1: Introduction

Policymakers and higher education institutions are increasingly interested in using disruptive innovations to increase access to high-quality, affordable higher education, yet little systematic research on the topic exists. This paper exploits the diffusion of the free and open college-level Internet courses known as Massive Open Online Courses (MOOCs) across various types of traditional 4-year institutions to enhance our understanding of what aids and hinders the systematic adoption of a disruptive innovation. The present project examines the extent to which different mechanisms and institutional characteristics influence the adoption of a disruptive innovation over time and by type of institution to shed light on a growing policy problem: how to effectively stimulate innovation in higher education in order to increase the number of college graduates in a more affordable way (Lederman, 2016; Lederman & Fain, 2017).

According to the U.S. Department of Education (2016a), three-quarters of the fastest-growing occupations require education and training beyond a high school diploma, but nearly half the students who begin college in this country will not finish within 6 years. At the same time, rising tuitions are putting college out of reach for families striving to move up to the middle class. Between 2004-05 and 2014-15, prices for undergraduate tuition, fees, room, and board at public institutions rose 33%, and prices at private nonprofit institutions rose 26%, after adjustment for inflation (National Center for Education Statistics [NCES], 2016). Given these statistics, during his 8-year term as president, President Obama made increasing access to and affordability of higher education the centerpiece of his higher education agenda (Black & Furman, 2016; Lederman & Fain, 2017; U.S. Department of Education, 2011, 2016a, 2016b).

To steer the country towards increased college completion, in his first major speech to Congress, President Obama outlined a national strategy to achieve the highest proportion of

college graduates in the world by 2020. The administration said it would provide students with the necessary support to complete college, whether that be a “community college or a four-year school, vocational training or an apprenticeship” (Lederman & Fain, 2017) Citing the fact that the United States had fallen to 13th place globally in the proportion of postsecondary attainment, President Obama said that reversing this trend was a matter of economic necessity: “America cannot lead in the 21st century unless we have the best educated, most competitive workforce in the world” (U.S. Department of Education, 2011).

The administration adopted and implemented solutions to help students as well as institutions to dissolve these barriers. In terms of policy, the Obama administration took significant steps to increase college affordability for students through increasing the award size of Pell Grants by \$1000, issuing tax credits, and reforming the loan programs (Black & Furman, 2016). To increase the attainment of a postsecondary credential on the student side, one of the defining strategies that the administration took was to promote disruptive innovation in higher education (Black & Furman, 2016; Lederman, 2016; Lederman & Fain, 2017). Where *innovation* is the adoption of a new idea or practice (Rogers, 1983), *disruptive innovation* is the adoption of simpler and more affordable product or service that transforms a sector over time (Christensen, Horn, Caldera, & Soares, 2011). According to the former Under Secretary of Education Ted Mitchell, the administration took the approach that more and better alternatives to traditional institutions were needed in order to transform traditional higher education (Lederman, 2016). For example, the administration supported the emergence of alternative training programs by freeing up federal financial aid for experimental programs such as coding boot camps, online course providers, and even General Electric (Fain, 2016).

Disrupting innovations are often juxtaposed to *sustaining innovations*, innovations that drive up prices by delivering better services or products for mainstream customers (Christensen & Weise, 2014). By contrast, disruptive innovations are those which serve a new market through the creation of a new kind of product that may be initially worse than the prevailing product or service, as judged by performance metrics, but addresses the needs of a new market (e.g., new market of students yet to get a postsecondary education) (Christensen & Eyring, 2011; Christensen & Horn, 2013). According to some researchers, sustaining innovations in higher education may include replacing full-time faculty with adjuncts or reducing the number of teaching assistants per class of students (Brewer & Tierney, 2010; Ehrenberg, 2006; Zusman, 2005). While it is debatable whether these changes are “better” compared to what was available before, they are nonetheless innovations designed to cut costs and deliver a more affordable education to students. Advocates of disruptive innovation have argued that dependence on sustaining innovations rather than disruptive innovation means that the sector as a whole has not dramatically increased the system’s ability to educate more students or drive costs down (Brewer & Tierney, 2010; Christensen & Eyring, 2011; Christensen, Horn, & Johnson, 2008).

Although many bemoan the lack of disruptive innovation in higher education (Diamond, 2006; Kirschner, 2012), little research exists on the drivers of systematic disruptive innovation. Some authors have pointed out that research tends to favor the “demand side” (e.g., the student) over the supply side (e.g., the institutions) (Baum, Kurose, & McPherson, 2013; Brewer & Tierney, 2010). That is, significant body of research on the demand side exists that shows improving access to loans and grants is effective in raising the rates of college enrollment because it makes college more reachable (see Dynarski, 1999; Dynarski & Scott-Clayton, 2013), but very little research is available on the “supply side,” especially regarding which instruments

effectively incentivize systematic innovation across traditional 4-year colleges and universities to improve quality and cost. In fact, Brewer and Tierney (2010) stated that it was “virtually impossible to ‘test’ competing explanations for why or how innovation takes place in the sector” (p. 12).

In practice, the lack of research on *systematic* disruptive innovation means that researchers and policymakers have a poor grasp of what aids and hinders adoption of disruptive innovation across different types of institutions, which impacts not only the effectiveness of policy designed to incentivize change but also, ultimately, the students in terms of equal access to high-quality, affordable education. For instance, Darrell Steinberg, the former California Senate President pro Tempore, proposed SB 520 in February 2013 to create a statewide network of low-cost online college courses for credit (SB 520, 2013). The bill was intended to relieve the bottlenecks caused by impacted courses, but it stalled in the Senate amid significant faculty resistance and concerns over faculty autonomy and control over what was being taught (Kolowich, 2013b; Says, 2013). Although this resistance came primarily from faculty in the case of SB 520, the responses may be symptomatic of not understanding the institutional context in which major transformative changes are being pushed.

Understanding the context in which an innovation takes place plays a critical role in achieving effective policy. The system of higher education includes various institutions that are defined by their own institutional characteristics and affected by the external environmental forces in unique ways. The combination of internal characteristics and influential external forces results in varying institutional responses (Brewer, Gates, & Goldman, 2001; Ehrenberg, 2006; Kezar, 2001; Slaughter & Rhoades, 2004). For example, when a shift towards neoliberal policy pressed the state and federal governments to cut higher education funding, public institutions

were more adversely affected than private nonprofit institutions (Slaughter & Leslie, 1997). Public institutional response in the face of lost state appropriations was to seek out revenue from the market. This example is of a coarse metric, but there are many more nuanced differences between various traditional colleges and universities that make it difficult to understand the ways in which different members of a complex system adopt a disruptive innovation.

An examination of the research provides at least two very compelling reasons for why traditional higher education institutions are motivated to change: (a) economic competition for increased revenue (Christensen & Eyring, 2011; Ehrenberg, 2006; Slaughter & Leslie, 1997; Slaughter & Rhoades, 2004; Zusman, 2005) and (b) competition for prestige (Brewer et al., 2001; Christensen & Eyring, 2011; Volkwein & Sweitzer, 2006). The Obama administration as well as other state governments, as discussed in more detail in Chapter 2, have often relied on economic competition from alternative providers for student markets to induce change (Bowen, 2015; Brewer & Tierney, 2010; Carey, 2015; Christensen & Eyring, 2011; Christensen & Horn, 2013; Fain, 2016; Lederman, 2016; Lederman & Fain, 2017; J. Selingo, 2013). Yet, if the research on higher education shows that the macro-institution encases microcosms of colleges and universities that respond in different ways to their environments, then using such a blanketed economic competition strategy to induce competition from providers may not provide the desired results of improved access to high-quality, affordable education. To date, no study has tested the extent to which different mechanisms of change affect the adoption of a disruptive innovation and why.

To enhance our knowledge of the underlying drivers of disruptive innovation in higher education and how these vary across different institutional types, this dissertation investigated the diffusion of massive open online courses from academic year (AY) 2011-12 to AY 2014-15.

MOOCs are free or low-cost internet-based university courses open to anyone (Waks, 2016). According to the definition of disruptive innovation, two components make MOOCs a disruptive innovation. First, they introduce more convenient and affordable products or services to students, compared to traditional provisions of postsecondary education. Second, they create pressure from the bottom-up to transform the existing top-down model of higher education over time (Christensen & Horn, 2013). Even though MOOCs are often conflated with online education, they are not the same. Online education usually combines elements of face-to-face instruction and online materials; courses have capped enrollments; and they usually are the same price as a traditional face-to-face course (Rhoads, 2015; Waks, 2016). By contrast, MOOCs include no face-to-face instruction; the materials are all online; they have no enrollment caps; and they are free to take.

The adoption of MOOCs was rapid and far-spread across many different kinds of institutions. Sebastian Thrun at Stanford University designed and launched the first MOOC, *An Intro to Artificial Intelligence*, in August 2011. In under two years since their introduction, more than 1,200 MOOCs have been developed (Shah, 2013). *The Wall Street Journal* reported that Coursera, a for-profit MOOC provider, had attracted over five million users, while edX, a nonprofit partnership between MIT and Harvard, had enrolled more than 1.3 million users (Fowler, 2013). In 2014, the number of universities offering MOOCs doubled to 400 and the number of courses also doubled to 2,400 (Shah, 2014). By the end of 2016, more than 58 million students enrolled in at least one MOOC, 700 universities adopted MOOCs, and more than 6,850 courses were offered worldwide (Shah, 2016). The types of adopters varied too. Public institutions, those owned by the state, and private nonprofit colleges and universities

adopted MOOCs. Also, elite and highly exclusive institutions (e.g., Harvard University) as well as less selective institutions (e.g., Missouri State in Springfield, Missouri) also adopted MOOCs.

The degree to which MOOCs have penetrated the system of higher education, where the system is many different kinds of institutions, shows that higher education is adaptable, responsive, and willing to engage disruptive innovation. The emergence of MOOCs renders an important opportunity to examine systematic innovation over time, allowing researchers to identify the ways in which different drivers affect different subgroups of innovation. Their diffusion is easily captured for research purposes since their origins started with an online platform with a web footprint from day one, which enables analyses that illuminate the ways in which the systematic adoption of a disruptive innovation takes place. Thus, this research took advantage of the rapid expansion of MOOCs across the system of higher education to investigate the drivers of disruptive innovation, how the drivers vary over time, and how the drivers vary by institutional type. The goals of this study are to provide policymakers with important information about the factors that affect the adoption of a disruptive innovation and to improve on the existing theory of how disruptive innovation diffuses in higher education.

Research Questions

Since the science of disruptive innovation is somewhat rudimentary, this dissertation examined the diffusion of innovation in a purposeful sequential order to develop the research on disruptive innovation in higher education. To build a foundation, I first examined which drivers, holding all else equal, affect the adoption of MOOCs. In the second analysis, I further developed the understanding of how characteristics of innovators change over time by analyzing the relationship between drivers and the partnership with for-profit or nonprofit MOOC providers, the platform through which universities launch MOOCs. This analysis plays a pivotal role in

understanding the extent to which variation in institutional characteristics affects when certain institutions over others adopt MOOCs and the ways in which they adopt MOOCs. Finally, while researchers typically use a classification schema to understand a phenomenon such as Carnegie Classifications, Barron's Selectivity Index, or public versus private, given the lack of a classification model for "types of institutional innovators," the third investigation analyzed the extent to which a typology of institutional innovators exists and how MOOC adoption is affected by group membership.

The research questions investigated in this study are:

1. When is MOOC adoption most likely? How does prestige-seeking behavior compared to economic competition influence the adoption of MOOCs?
2. Does partnership with a for-profit versus nonprofit provider differ by prestige-seeking behavior or economic competition? Do these partnerships change over time?
3. To what extent does a typology of institutional innovators based on prestige-seeking behavior and economic competition exist? To what extent does this typology of innovators relate to MOOC adoption? How does the adoption of innovation by institutional subgroup vary over time?

Theoretical Approach and Conceptual Framework

Why some institutions adopt a disruptive innovation while others do not is not clear. Only one theory, to my knowledge, has sought to explain disruptive innovation explicitly: Clayton Christensen's *Theory of Disruptive Innovation*. According to this theory, disruptive innovation is a product or service that takes root initially in simple applications at the bottom of a market and then relentlessly moves up-market, eventually displacing established competitors (Christensen Institute, 2017). In their 2011 book titled *The Innovative University: Changing the*

DNA of Higher Education from the Inside Out, Christensen and Henry Eyring postulated that by increasing competition from nontraditional providers such as for-profit colleges or online start-ups, traditional 4-year colleges and universities would be compelled to change. Some authors have tried to explain the diffusion of MOOCs using this theory (Yuan & Powell, 2013), but the theory was found to be deficient in its application to MOOCs because MOOCs had no business model when they emerged (Horn, 2014). According to Horn, a business model plays a key role in the theory of disruptive innovation because it allows a disruption to be sustainable and move up-market over time. Without it, then long-term sustainability is not guaranteed, allowing traditional leaders to retain control over the market.

Although the theory of disruptive innovation was not a strong explanatory model for the case of MOOCs, two other theories of *innovation* in higher education may be better frameworks for trying to explain *disruptive innovation* in higher education, and more specifically for the case of MOOCs: prestige seeking and academic capitalism. In higher education, some research has suggested that institutions innovate in order to increase their prestige (Brewer et al., 2001; Volkwein, 1987). Institutions are prestige maximizers because prestige engenders resources and high demand for their seats (Brewer & Tierney, 2010; Slaughter & Rhoades, 2004). Prestige is a zero-sum game, where as one institution gains more prestige, another one loses its prestige. According to this theory, prestige seekers are likely to innovate in order to displace other more prestigious institutions.

At the same time, some researchers have found that higher education is increasingly responsive to market forces and revenue generation, especially as public funding becomes scarcer and as the economy becomes more knowledge-based (Slaughter & Rhoades, 2004). In comparison to the prestige-seeking theory of innovation, the theory of academic capitalism

suggests that economic competition drives institutions to innovate (Slaughter & Rhoades, 2004). In this case, institutions that are driven by revenue generation are likely to innovate because it is another way to break into a new market. While the prestige-seeking and academic capitalism theories are not necessarily exclusive, they do posit different drivers of change. Neither the prestige-seeking nor academic capitalism frameworks, to my knowledge, have been applied to the diffusion of a disruptive innovation nor have they been applied to a quantitative dataset. The application of these theories to a new dataset that I constructed on the diffusion of MOOCs is one of the major contributions of this study.

In order to make headway in this new area, I borrowed from a framework that has been applied and tested in many political science cases to explain the adoption of a new policy or program: the diffusion of policy innovations (Berry & Berry, 2014; DiMaggio & Powell, 1983). According to this framework, political scientists have found that internal determinants (e.g., social, political, and economic drivers of change) and mechanisms of diffusion that reflect interorganizational pressures to change (e.g., imitation, competition, coercion, normative pressures, and learning) explain the adoption of innovation. Thus, under the assumption that these two components (e.g., internal determinants and mechanisms of diffusion) can be used to explain adoption of an *innovation*, I strove to explain the adoption of a *disruptive innovation* using the economic competition and prestige-seeking theories of change in higher education. Specifically, the mechanism of diffusion is competition—but I compare the characteristics of economic competition to those of competition for prestige. By using these mechanisms of diffusion plus indicators of institutional adoption, I am able to explain better what drives higher education institutions to adopt a disruptive innovation. This policy diffusion framework is discussed in more detail in Chapter 2.

Empirical Approach

One of the largest contributions of this study is the creation of a new dataset that merges institution level data with MOOC data. Financial and institutional characteristics data come from the Integrated Postsecondary Education System (IPEDS) (NCES, 2017c), sponsored by the National Center for Education Statistics. MOOC data come from a website that aggregates all MOOC data called Class Central (Class Central, 2016). Because I was interested in examining what causes institutions to change state (e.g., from a non-disruptive innovator to a disruptive innovator), I examined only first-time adoption patterns. Additionally, while some community colleges have adopted MOOCs, I excluded them for several reasons explained in more detail in Chapter 3. The sample used in this study included only 4-year, nonprofit higher education institutions ($n = 1,470$). Because I was examining what drives change in traditional higher education, I selected only the nonprofit institutions.

Analytic Approach

This research required several different methodological approaches to examine the institutional adoption of MOOCs. First, political scientists use event history analysis models to describe the impact of jurisdictional characteristics and mechanisms of diffusion on the propensity of jurisdictions to adopt a new policy. I applied a similar approach to the adoption of MOOCs in higher education. I used institutional characteristics plus the mechanisms of diffusion to determine the propensity of 4-year higher, nonprofit, private, and public institutions to adopt MOOCs. The type of event history model that I employed is called a discrete time hazard model (DTHM), which divides the analysis of the likelihood of adopting a new innovation into years. This method is used commonly in social science research to examine whether a particular event is likely to occur in a given period of time and why (Singer & Willett, 2003). In my analysis, the

DTHM provides the likelihood that an institution will adopt a MOOC in a given year. Since current research on the likelihood of adopting MOOC is nascent, this is the first contribution of this study.

The advantage of the first model is that we learn maximum likelihood of institutional adoption of MOOCs and what drivers are more strongly predictive of adoption. However, this model does not necessarily show differences among groups of adopters; rather, it highlights the most prominent attributes that distinguish adopters from non-adopters. However, as organizational change scholars have also pointed out, not all institutions adopt innovations instantaneously or have the same motive (Cyert & March, 1963; Rogers, 1983). To draw out these differences, I used descriptive statistics to analyze how the incentives changed over time among just the adopters and whether these incentives varied by whether the institution partnered with a for-profit or nonprofit provider ($n = 122$). Institutions have a choice of partnering with for-profit versus nonprofit providers and because institutions have varying capacity to innovate, there may be a different drive to innovate (i.e., some may be more driven to generate revenue or the pursuit of prestige), which can be elicited by studying changes in institutional characteristics over time and changes in partnerships over time. By examining the data in this way, we learn the ways in which disruptive innovation diffuses across institutions with different characteristics and behaviors.

Finally, in the last question, I conducted a latent class analysis (LCA) to examine the extent to which a typology of institutional innovators exists. The first two models suggest there exist innovators and non-innovators that are separated by different degrees of prestige and competition as well as capacity to innovate, yet we have no working classification model of institutions that adopt disruptive innovations. In order to elicit groups statistically that are thus

far unobservable, I employ an LCA. The LCA model posits that there are two or more subgroups in a population, and subgroup membership must be inferred from responses on multiple items (Jung & Wickrama, 2008; Lanza, Tan, & Bray, 2013). In this procedure, the focus is on the relationship among cases, and the goal is to classify cases into distinct groups or categories based on their response patterns so that institutions within a group are more similar than institutions between groups (Jung & Wickrama, 2008). I used this tool because the findings from the first and second analyses produced empirical differences that were not observable in the currently available typologies of institutional categorization (i.e., Barron's Selectivity Index, Carnegie Classifications, and other metrics of classifying higher education). By creating these subgroups, we learn about inter-institutional differences to improve our understanding of what aids or hinders systematic adoption of an innovation.

Chapter Overview

Four chapters follow this introduction. Chapter 2 reviews literature that provides important context in which adoption has taken place. It also provides a more detailed outline of the evolution of the theories and why my research is novel for comparing competing incentives of change. Chapter 3 provides an in-depth discussion of the data sampling and methods employed in this dissertation. Chapter 4 reports on the findings for all three questions. Finally, Chapter 5 includes a summary of the findings, an in-depth discussion of the policy implications, limitations, and future areas for research.

Operational Definitions

- Adoption: The process by which a technology innovation is chosen for use by a university.

- Diffusion: The process by which “an innovation is communicated through certain channels over time among the members of a social system” (Rogers, 2003, p.5).
- Disruptive Innovation: According to Christensen, Horn, Caldera, and Soares (2011) disruptive innovation is the process by which a sector that has previously served only a limited few because its products and services were complicated, expensive, and inaccessible, is transformed into one whose products and services are simple, affordable, and convenient and serves many no matter their wealth or expertise. (p. 2)

The product or service takes root initially in simple applications at the bottom of a market and then relentlessly moves up-market, eventually displacing established competitors (Christensen Institute, 2017). In education, this innovation is cheaper and more accessible to nontraditional students. Ultimately, a disruptive innovation is an innovation designed to save students time and money (Christensen and Horn, 2013).

- Innovation: An idea, a practice, or object that is perceived as new by an individual or other unit of adoption (Rogers, 2003, p. 12).
- Institution: Throughout this document, the word *institution* refers to colleges and universities.
- MOOC: A Massive Open Online Course is free, open to the public, and does not have any admissions criteria. Grading may be done by machines or people.
- New Economy: The post-industrial economy in which knowledge is treated less as a public good than as a commodity to be capitalized on in profit-oriented activities (Slaughter & Rhoades, 2004). I use this synonymously with knowledge-based economy.

Chapter 2: Background and Conceptual Framework

This study used the expansion of MOOCs to shed light on how systematic disruptive innovation takes place in higher education. This literature review provides an important context for the rise and expansion of MOOCs in U.S. higher education and introduces different external and internal pressures for institutions to change. First, I broadly discuss the political and economic environment of higher education that laid the groundwork for early technological innovation and, eventually, MOOCs. Then, I discuss in more depth the origins of open courseware (OCW) and open educational resources (OER) and the origins of MOOCs to highlight institutional motivations to adopt such open educational resources. Finally, I review the relevant theoretical constructs for understanding institutional change and lay out the theoretical tenets I employed to analyze the adoption of MOOCs. Search engines included Google Scholar, ERIC, Columbia University Library Online, and Teachers College searchable online index. Key search terms included Open Courseware, Open Educational Resources, adoption/diffusion, technological innovation, instructional technology, learning management system (LMS), neoliberal, MOOCs, institutional theory, and innovation agenda.

Changing Political Economy of Higher Education

Pressure to innovate has been growing since the early 1990s, when changes in the political and economic spheres urged governments to change their approach to higher education (Alexander, 2000; Altbach, Gumport, & Berdahl, 2011; Gumport & Sporn, 1999; Slaughter & Leslie, 1997). In general, there was a dramatic shift from an industrial-based economy to a knowledge-based economy, in which knowledge is treated as a resource that can be capitalized on in profit-oriented activities (Slaughter & Rhoades, 2014). Abroad, governments were investing in higher education, gaining a competitive economic edge. Hence, to compete, the U.S.

government turned to higher education to play a pivotal role in educating more workers and to transform the economy into a technology-based economy. Specifically, the U.S. government looked to the postsecondary sector to improve workers' skills as well as their ability to develop and use technology to enhance productivity and strengthen the state's economic position (Alexander, 2000).

While pressure to educate more workers rose, a neoliberal shift in the political economy catalyzed a change in the way the government managed the public sector, including higher education. Under these conditions, governments were pressed to increase efficiencies and contain taxes (Olssen & Peters, 2005; Zumeta, 2001). According to the literature, rising concerns over government expenditures led federal and state governments to divert funds from higher education to entitlements like Medicare and Social Security, K-12 education and prisons (Alexander, 2000; Baum et al., 2013; Gumport, Iannozzi, Shaman, & Zemsky, 1997; Slaughter & Leslie, 1997). This effectively required higher education to do more with less, and the current prevailing theory is that the accountability movement has required public higher education to do more with less ever since (Altbach et al., 2011; Dougherty et al., 2016; Mettler, 2014; Slaughter & Rhoades, 2004). At first, part of this move towards greater accountability stemmed from public dissatisfaction with higher education. King Alexander (2000) noted that the public had become increasingly resentful of higher education's exclusivity and limited value proposition. Many perceived that the institutions were locked away in their "Ivory Towers," denying access to the average worker. They were viewed as nonresponsive to societal and economic demands. King further noted that the source of resistance stemmed from how traditional measures of institutional performance and effectiveness, including peer review and market choice, were no longer sufficient indicators of institutional value. Other authors have suggested that shortcomings

in management and accountability, on which public funds were dependent, were not showing strong enough returns (Gumport et al., 1997; Zumeta, 2001). Thus, government pushed for greater efficiency and productivity. By cutting public funding to higher education, the government reasoned that higher education institutions would become more efficient and accountable to state demands out of necessity (Gumport et al., 1997).

Although increased accountability began in the 1990s, it still forms a key part of federal policies today. The Obama administration focused on improving accountability through a number of actions focused on outcomes. For example, several regulations were passed to rein in college costs and improve student outcomes: (a) Gainful Employment regulations stopped the flow of federal dollars to low-performing career colleges; (b) the College Opportunity and Graduation Bonus rewarded colleges for enrolling and graduating significant numbers of low-income students; and (c) the College Scorecard was a consumer tool that rated colleges according to graduation rates, total college costs, average debt load, and even earnings 10 years after graduation (Turner, 2015; U.S. Department of Education, 2016a).¹

¹ To date, no action has been taken to roll back these higher education regulations put in place to improve college accountability. However, GOP lawmakers have been clear since the election in November 2016 about their plans to dismantle several higher education regulations instituted by the Obama administration, including two major rules aimed at the for-profit college sector (Kreighbaum, 2017). The first rule that the Trump administration will try to roll back is the Borrower Defense rule, which clarifies how defrauded borrowers can seek discharges of their student loans. The second is the Gainful Employment rule, which was designed to penalize vocational programs that leave graduate students with more loan repayments that exceed 8% of their total incomes. In a recent report, 800 institutions were found to be in violation of the Gainful Employment rules, where annual loan payment exceeded 12% of total earnings. The vast majority of these institutions were for-profit colleges (98%) (U.S. Department of Education, 2017). Although President Trump is likely to roll back the regulations aimed at for-profits, others are not sure whether he will proceed because he campaigned on cutting waste, fraud, and abuse of government funds—all of which the for-profits have engaged in (Kucinich, 2017).

Higher Education Economic Constraints

While increased accountability was intended to increase efficiency and productivity in higher education, the results have led to serious institutional economic constraints. For one, because policies could not keep up with the expansion, institutions responded by privatizing and taking other actions to cut costs (Slaughter & Leslie, 1997; Zusman, 2005). For example, institutions engaged in redistributing institutional funds from less marketable areas to more marketable areas (e.g., from humanities to the biosciences) (Slaughter & Leslie, 1997) and increased supply of instructors to match increased student enrollment while tenure-track opportunities declined (Ehrenberg & Zhang, 2007). Moreover, when governments encouraged tying funding to outcomes (e.g., performance funding), other negative consequences ensued; specifically, some institutions restricted students who needed remedial assistance (Ehrenberg, 2006; Zusman, 2005) while others narrowed their academic missions (Dougherty et al., 2016; Lieberwitz, 2005). Universities also increased tuition to offset losses in state and federal appropriations, which then prompted more stringent government oversight for the use of federal student aid (Alexander, 2000). This cycle seemed endless. Ultimately, although government was focused on increasing accountability, higher education financing had become much more dire.

Then, the Great Recession of 2008 pummeled higher education (Rhoads, 2015). It led to massive state-level spending cuts and changes to federal aid, impacting both institutions and students. According to a report from the Center on Budget and Policy Priorities (Mitchell, Palacios, & Leachman, 2014), as of 2014, states on average had cut spending by 23% of pre-Recession levels, and the majority of states (48/50) were still spending less per student than they did pre-Recession. Moreover, when states cut funding, universities and colleges either had to cut educational or other services, raise tuition or do both simultaneously to compensate for the losses.

Mitchell et al. reported that since the 2007-08 school year, annual published tuition has risen by approximately 28% nationally (or \$1,936 on average). Arizona, the state with the greatest tuition increases, rose 80.6% or \$4,493 after inflation.

At the same time tuitions were rising, student debt had risen to historic levels. By 2014, student debt had exceeded \$1.08 trillion, of which 11.5% was 90 or more days delinquent (Touryalai, 2014). With rising tuition and fear of debt, students became more price-conscious and began pursuing more affordable options, especially community colleges (Dunbar et al., 2011; Vise, 2011). As students changed preferences on the type of college to enroll in, some private nonprofit 4-year colleges indeed saw their enrollments drop, though modestly (Dunbar et al., 2011). These drops caused institutions to be even more vulnerable to losses of funding (Waks, 2016).

A Federal Higher Education Innovation Agenda and Economic Competition

The Obama administration made the expansion of postsecondary education a centerpiece of his higher education agenda from the outset (U.S. Department of Education, 2011). In his first few weeks in office, the president proposed the College Completion agenda, where by 2020 the United States would have the world's highest percentage of adults with a postsecondary education (Lederman & Fain, 2017). The U.S. Department of Education predicted that over the next decade, the share of jobs requiring some level of higher education would grow rapidly, with 11 of the 15 fastest-growing occupations requiring postsecondary education (U.S. Department of Education, 2016a). The Obama administration took several actions to induce evolution and innovation in higher education (Lederman, 2016; Lederman & Fain, 2017; U.S. Department of Education, 2011).

Arguing that college affordability presented one of the biggest obstacles to achieving this 2020 Completion goal (U.S. Department of Education, 2016a), President Obama attempted to increase affordability in two ways: providing better student aid and increasing competition to drive innovation in higher education. For students, he signed laws that lowered loan interest rates, raised the maximum amount awarded in Pell Grants, introduced new education tax credits, simplified the FAFSA to apply for student aid, increased GI funding, and made loan repayments more manageable by capping monthly payments as low as 10% of their monthly income (Black & Furman, 2016). The president also proposed the America's College Promise, which would make 2 years of community college free for responsible students to earn critical workforce skills and the first half of a bachelor's degree at no cost (U.S. Department of Education, 2016a).

The literature reveals that in order to drive costs down on the institutional side, the Obama administration relied primarily on incentivizing innovation through economic competition. While traditional 4-year institutions had historically dominated the provision of higher education, the rise of new technologies in online education paved the way for alternative providers to emerge (e.g., for-profit online education providers, coding boot camps, and competency-based education) (Waks, 2016). To foster growth from alternative providers, the Obama administration provided financial support and incentives. For example, in 2013, a new, alternative system of accreditation provided pathways for higher education models and colleges to receive federal student aid based on performance and results (Carey, 2013). Because the accreditation system ultimately controls access to 140 billion dollars dispersed in loans and grants by the federal government, the proposal would have created a level playing field for businesses that provided higher education services but were not traditional colleges.

The Obama administration also used competition for grants and federal student aid dollars to encourage experimentation with new models of teaching, costs, and educational and employment outcomes for student experiments. For example, in 2015, Obama announced the creation of the Educational Quality Through Innovative Partnerships (EQUIP), a coalition of traditional colleges and universities partnerships with nontraditional providers to achieve better student outcomes. The plan frees federal financial aid for non-college job training, including offerings by coding boot camps, online course providers, and General Electric. In August 2016, the U.S. Department of Education (2016a) solicited eight selected partnerships between institutions of higher education and nontraditional providers to participate in the EQUIP experiment.

The advent of new technologies enabled the rise of alternative provisions to traditional higher education. The Obama administration latched on to these developments to encourage further innovation in institutional innovation and often relied on market mechanisms to compel institutions to innovate. Although using technology to challenge the status quo on provision of education became a mainstay of Obama's years as president, developments in technology had actually already led to important experiments with the provision of education in the early 2000s. This is discussed in more detail in the next section.

MOOC Antecedents

By the mid-2000s, for-profit higher education had already developed a robust distance education program that boasted a market of hundreds of thousands of students (Apollo Group, n.d.). However, traditional higher education still largely opposed distance education for fear it would jeopardize its reputation and exclusivity (Kirp, 2004; Walsh, 2011). Nevertheless, against a backdrop of increased accountability, economic constraints, and pressure from the federal

government to adopt innovation, a few pioneers in traditional higher education (i.e., nonprofit, 4-year higher education) began experimenting with new ways to provide education via the Internet.

Two types of open education emerged: open courseware (OCW) and open educational resources (OER). OCW is a free and open digital publication, delivered as an online course, of high-quality college- and university-level educational materials (OCW, 2017). OERs, by comparison, are any type of educational materials available to the public that anyone can legally and freely copy, use, adapt and re-share (UNESCO, 2017). OERs encapsulate a broader range of educational materials than OCWs, such as textbooks, curricula, lecture notes, assignments, tests, projects, audio, video, and animation. In practice, the two terms are usually treated synonymously.

One of the most comprehensive reviews of the rise and expansion of open educational resources in the literature is Taylor Walsh's (2011) study of elite universities' early uses of the Internet to publish core undergraduate course materials. Walsh reviewed the goals and sustainability of online course initiatives for the following programs: Fathom Partners by Columbia University; All Learn by Oxford, Princeton, and Stanford Universities; Open Yale Courses by Yale University; Open Learning Initiative by Carnegie Mellon; OpenCourseWare by MIT; Webcast.edu by University of California Berkeley; and one foreign program, National Programme on Technology Enhanced Learning (NPTEL) by the Indian government. Not all of the programs were open, however. Some like Fathom and All Learn charged fees for their materials, while others such as OpenCourseWare were free. The motives and strategies for reaching students varied for each institution, suggesting that some institutions were motivated more by market forces while others were more motivated by a democratic mission to make elite

undergraduate education more accessible. I reviewed Walsh's findings for Columbia, Carnegie Mellon, and Berkeley because their characteristics most aligned with MOOCs, compared to the others.

One of the first institutions to adopt open online education was Columbia University, which in 1999 launched Fathom Partners, a separate, profit-seeking entity designed to generate revenue for the university and strengthen its name. According to Walsh (2011), Columbia wanted an early stake in making its courses widely available online. The Provost publicly acknowledged that the goal was to be entrepreneurial because the university had been giving away education for generations and wanted a return on its investment (p. 28). Since Columbia had already demonstrated it could successfully earn income from patents and licensing technologies, its leaders thought that lectures could engender the same level of profits if monetized correctly. Despite their success in the private research world, Fathom never attracted enough paying customers to sustain its operations. Even after shortening, cheapening, and simplifying their courses, their model ultimately failed to succeed. According to an interview with Anne Kirchner, the chief executive of Fathom and professor of English at Columbia, Fathom faced inherent contradictions that made carrying out its objective difficult—namely, having a foothold in both the for-profit and not-for-profit camps. On one hand, Fathom sought to democratize education; on the other hand, it needed to be profitable. Kirchner argued that profit making was limited by Columbia's need to be a good steward of its brand and intellectual property. Other institutional start-ups met a similar fate as Fathom did. Profit-seeking institutions were not very successful; for example, All Learn ultimately failed to become self-sustaining. The point to be taken from these lessons is that maintaining prestige may be orthogonal to profit making and economic competition.

Despite the failures of All Learn and Fathom, other start-ups were successful. For instance, MIT, Carnegie Mellon, and Berkeley started programs that are still running to this day. The major difference, discussed below, is that these organizations were not driven by profit making, but by expanding research on teaching and learning in an online setting. The first to launch a successful program was MIT with its OpenCourseWare (OCW), a nonprofit entity, in 2001. The organizational mission was to make freely available web-based versions of course materials, including syllabi, lecture notes, reading lists, assignments, videos, and other content related to the course. By the time of Walsh's study in 2004, OCW had published the curriculum from over 2,000 courses, including every course offered by MIT, although course content was not uniform.

According to Walsh's study, MIT originally developed OCW in order not to be eclipsed by other institutions developing open online courses. Like the other models, MIT also assumed that their version would be revenue-generating. However, when MIT was in the beginning stages of developing its online content, it simultaneously hired a consulting firm to analyze why Fathom and All Learn had failed. Per the firm's recommendation, MIT decided to offer the courses for free instead of charging as Fathom and All Learn did. Ultimately, according to Walsh, the university determined that its success was due to its decision to not charge. Without a fee, the university could form personal relationships with foundation leaders that resulted in "an extraordinary amount of start-up funding" (p. 57). For example, The Hewlett and Mellon Foundations initially committed \$11 million and \$15 million, respectively, after seed money (as of Walsh's 2011 report). By offering free courses, MIT demonstrated its commitment to advance human capital in places within and beyond its reach.

MIT also argued that faculty buy-in was critical to the success of OCW, which was originally designed as a repository for all university courses at MIT. In order to create such a large repository of information, OCW needed both an orderly operation and buy-in from the MIT faculty. Before its launch, a core group of faculty responsible for strengthening OCW began an exhaustive internal communications campaign to increase faculty support, and the team in charge expected faculty resistance to sharing materials openly. Surprisingly, as Walsh reported, MIT did not encounter significant resistance, and the MIT faculty voted to participate in the initiative in February 2001. The most willing professors, who were often members of the planning commission, began by publishing their courses. To spur faculty participation, stipends of \$3,000 were initially provided to faculty, although they decreased over time until ending in 2006 after participation was common. MIT also attributed low faculty resistance to the fact that the administration did not sell OCW as a philanthropic mission, but rather as an opportunity to strengthen teaching and learning for its own students. The administration found that faculty needed a personal reason to share their coursework. Some faculty reported that they learned new and better ways to present material after reviewing their colleagues' lectures and course information. Also placing all materials into one repository meant that differences between upper- and lower-level courses were highlighted and weaknesses in material were exposed. The administration argued that this repository ultimately united the faculty.

MIT ultimately decided to expand its success with OCW to other institutions globally. The Johns Hopkins University, Tufts University, and Utah State University first joined, followed by others included in the discussion. MIT then realized it needed an organized platform for managing university participation; with funding from the Hewlett Foundation, MIT founded the OpenCourseWare Consortium (OCWC) in 2005. The goal was to “extend the reach and impact

of OpenCourseWare by encouraging the adoption and adaptation of open educational materials around the world,” “foster the development of additional OpenCourseWare projects,” and “ensure the long term sustainability of OpenCourseWare projects by identifying ways to improve effectiveness and reduce costs” (Walsh, 2011, p. 78). The Consortium currently includes hundreds of institutions of higher education with the greatest involvement from non-English-speaking regions, especially Asia. While the global response was high, U.S. institutions were not as keen to join OCWC. Walsh’s interviewees hypothesized that while some were drawn to the Consortium because of MIT’s name, others did not want to appear to be following MIT (p. 79).

In order to sustain its mission, MIT was and remains reliant on foundation and institutional grants because it is a nonprofit entity. It relies primarily on its espoused education benefits to teaching and learning in order to attract revenue that will support its ongoing commitment to making course information available. Still, as Walsh reported, the OCW team acknowledged it would still need to find alternative sources of revenue to remain viable and up-to-date.

Carnegie Mellon University, like MIT, also pursued another nonprofit, open courseware initiative called Open Learning Initiative (OLI), which it developed first and funded later. Unlike MIT, however, Carnegie Mellon created a platform that delivered the whole course with automated feedback. The creation of OLI signaled an important shift from a static platform to a dynamic one, in which students could see a lecture and receive automated feedback. When automatic, the feedback enables a lower cost of providing education because the human capital requirements are fewer. When done correctly, the course can provide users with self-contained rich online environments that guide users via interactive examples, embedded assessments, virtual labs, and constant feedback. The courses even included “mini-tutors” that give targeted

feedback to students answering practice questions. Taking advantage of its strengths in instructional design, cognitive science, software engineering, and human interaction, Carnegie Mellon's goal was to develop an online program that was highly effective and accessible to the masses. Because of these advancements, the OLI was also the only type of OER to receive recognition by the Obama administration. OLI was seen as a solution to educating more students without expending more resources. A budget for using freely available online education was even included in the budget for the Health Care and Education Reconciliation Act of 2010, but in the end it was eliminated.

Although the OLI made gains in making education more accessible and productive, scaling it was not feasible. First, the only courses available were in the sciences, math, and foreign languages, which were Carnegie Mellon's strengths. The OLI team was skeptical that their courses would be amenable to humanities, for which measuring skill acquisition was more difficult. But the team admitted it had not yet tested a humanities course. Additionally, while preliminary studies demonstrated that students' outcomes improved when they used the OLI, the price tag for making each high-quality course that ensured learning was very high: approximately \$500,000, with a tremendous investment of human labor. As well, finding the resources to support its development was challenging. Hewlett promised to fund the university's experiment if it kept its courses free and open to the public.² The university said that if it focused more on turning out a product, they could penetrate the market and become self-supporting. However, if they focused on commercializing the product and used venture capital to launch a

² According to their website, it appears the Hewlett Foundation is still funding the initiative (Carnegie Mellon University, 2017).

large-scale production, the university worried it would be forced to focus on what would sell instead of what would help students.

Finally, while OLI was a very expensive production, Berkeley produced another, far less expensive online lecture alternative, but with fewer bells and whistles. In 1995, Berkeley began video recordings of its lectures and, in 2001, formalized this production under Education Technology Services (ETS), giving it the name [webcast.berkeley](http://webcast.berkeley.edu). By 2010, [webcast.berkeley](http://webcast.berkeley.edu) offered almost 550 courses to the public through YouTube and iTunes, with a budget of only \$700,000. Berkeley funded these webcasts entirely on its own without support from big foundations in the field. The production was focused on efficiency and improving the student learning experience at Berkeley.

[Webcast.berkeley](http://webcast.berkeley.edu) is a repository of lectures that students can use if they want to review the lectures online, although others worldwide can also access them for viewing. The filming of the courses was inexpensive, especially compared to the cost of the other initiatives, because microphones and cameras were permanently installed in some of the lecture halls and software was written to initiate recordings and post them to the web automatically. Interestingly, unlike other universities that selectively curate their courses, Berkeley's choice of lectures to webcast was simply done according to whatever lecture the Registrar's Office assigned. Over time and especially after the Great Recession, Berkeley also began to see webcast.edu as a revenue generator. One provost even reported, "There's a huge, huge untapped market out there" (Walsh, 2011, p. 176).

Also, like MIT and Carnegie Mellon, the initial goal of [webcast.berkeley](http://webcast.berkeley.edu) was not to generate revenue but to build up public support. Walsh analyzed [webcast.berkeley](http://webcast.berkeley.edu) in the context of California's primary mandate for public colleges and universities to expand access within the

state. According to the California Master Plan for Higher Education, all students should be guaranteed access to either the University of California system, the California State University system, or the California Community College system based on their high school rankings. However, because of the state's financial situation and rising population, cutbacks caused the demand to outstrip the supply. In 2004 and again in 2008, California institutions turned down qualified applicants for the first time since the creation of the Master Plan. The public was increasingly dismayed and disappointed in the California higher education system. Former Executive Vice Chancellor and Provost of Berkeley Paul Gray noted that by making these courses available, they were returning on the public's investment and generating public good will. It was in the university's best interest to share webcast.berkeley with the public to create a sense of "shared ownership" and "shared benefit of public higher education" (p. 166). However, unlike MIT and Carnegie Mellon, in recent years Walsh also found that the university has considered commercializing webcast.edu in order to generate badly needed revenue after continued cutbacks in state appropriations. As of now, courses are still free.³

Walsh's review of the different ways universities have utilized the Internet to make their courses or course materials available was extremely instructive from the position of understanding the organizational impetus for adopting the first viable open education resources.

The incentives and goals varied considerably across the different campuses. Columbia with

³ In recent news on the webcast.berkeley program, University of California Berkeley has decided to cut off public access to the tens of thousands of lectures and podcasts in response to a U.S. Justice Department order that it make the educational content accessible to people with disabilities, specifically deaf and blind people. The university explained that the cost to make this free content compliant with the American Disabilities Act of 1990 would be extremely expensive to do. They explained courses would still be made available free via edX and those courses would be more accessible to persons with disabilities (Straumsheim, 2017).

Fathom and Stanford, Yale, and Princeton with All Learn were driven by economic competition and revenue generation, whereas MIT, Carnegie Mellon, and Berkeley were driven by improving research on teaching and learning. Ultimately, the nonprofit enterprises endured longer and were more successful in terms of expanding access to education.

Emergence of MOOCs

Similar to the rise of OER and OCW, the rise of Massive Open Online Courses (MOOCs) began with Stanford, Harvard, Berkeley, and MIT. The term had been coined earlier by George Siemens and Stephen Downes, two professors who hosted the very first, genuinely open online course in Manitoba, Canada, in 2008 (Rhoads, 2015). Siemens and Downes were focused on connecting students over a network in a course called cMOOCs, where ‘c’ stood for connectivist. However, American researchers were more interested in making high-quality education accessible to the masses without using networks for teaching and learning (Rhoads, 2015).

With the intention of making a course absolutely open, in August 2011, Sebastian Thrun, a professor of computer science at Stanford, launched the first xMOOC, which is now known more widely as just MOOC. According to the *New York Times*, Thrun’s course *Intro to Artificial Intelligence* enrolled more than 150,000 students in its very first launch. As Thrun started his own for-profit startup called Udacity, two other professors at Stanford, Daphne Koller and Andrew Ng, started Coursera, another for-profit MOOC startup. While Udacity made its own courses, Coursera partnered with universities to deliver courses. Coursera would act as the *provider* for an open-source platform to stream the course and house the technical components, while universities would be the *producers* of the courses. When it first launched its courses in the spring of 2012 with the original partners (Princeton, Stanford, and the University of

Pennsylvania), more than 1.7 million students enrolled. Then, in September of 2012, MIT and Harvard joined forces to create a nonprofit startup called edX. When edX launched, more than 370,000 students enrolled. Like Coursera, edX also partnered with universities, but Coursera contractually promised its partners that it would only partner with elite institutions to protect their brand (Rivard, 2013b).

The MOOC movement was far more successful in penetrating U.S. universities as well as universities around the world, compared to MIT's OCW. By 2013, more than 700 MOOCs were being offered, with more added every day (Shah, 2013). By the end of 2014, more than 400 universities worldwide had partnered with one or more of the MOOC providers, and they together with the providers had built an astonishing repository of more than 2,400 courses. Enrollments soared to somewhere between 16-18 million students (Shah, 2014). By 2016, more than 58 million students had signed up for a MOOC and more than 7,000 courses worldwide were offered (Shah, 2016). Compared to the OCW/OER movement, MOOCs had generated a much swifter response from the public and partnering institutions.

The rapid expansion gave way to fears and hope from others that traditional higher education would be dissolved. In a 2013 *Atlantic* article by Zachary Karabell titled "College Is Going Online, Whether We Like it Or Not," the digital disruption was reportedly "unstoppable," given rising tuition and debt (Karabell, 2013). Because of this, there was speculation that MOOCs would "disrupt education" by creating an alternative provision of education that would ultimately drive prices down (Carey, 2015; Christensen & Eyring, 2011; Christensen et al., 2011; Christensen & Weise, 2014; Selingo, 2013). Thrun predicted that in 50 years' time, the expansion of MOOCs would leave only 10 higher education institutions standing (Leckart, 2012). However, a number of articles have come out since suggesting that this frenzy was only hype

and MOOCs would not dissolve higher education. Instead, MOOCs are considered critical tools for understanding advancements in the ways Internet technologies can be used to improve teaching and learning (Horn, 2014; Kolowich, 2013a; McPherson & Bacow, 2015; Young, 2013).

Differences Between MOOCs and OCW/OER

Although it is widely agreed that OCW/OER laid the groundwork for MOOCs, they, unlike OCW, were developed specifically to bundle and sell education. In a blog piece titled “What’s the Difference Between OCWs and MOOCs? Managing Expectations,” David Wiley (2013) argued that MIT’s OCW and its followers have always positioned themselves as primarily “teacher-facing.” The materials were intended to support faculty who teach similar topics or be a source for group professional development. In other words, it was good if a learner benefitted from the course, but that was not the primary goal. By comparison, MOOCs, as Wiley argued, positioned themselves as primarily “student-facing.” The material was intended for use by students and not by teachers, as was the case with OCW. MOOC faculty have been widely prohibited from using their materials in the courses they teach, in part because the courses are proprietary information and designed to be packaged for sale. Building on this point, Rhoads (2015) claimed that OCWs never actually had the same earning potential of MOOCs *because* they were framed as part of the democratization of knowledge and information. By contrast, MOOCs attracted venture capitalists, entrepreneurs, and revenue-minded educationalists who were interested in creating conditions for revenue generation by online massification and provision of course credit (p. 17).

Another difference between OCW/OER and MOOCs was that more institutions were willing to partner with MOOC providers than with OER/OCW institutions (Rhoads, 2015). During the OCW/OER movement, only elite institutions experimented with using the Internet to

disseminate instructional material; by comparison, a much wider range of universities and colleges participated in expanding access to their curriculum with MOOCs. Moreover, institutions today are beginning to award credit for courses, whereas before they were unwilling to do so. Rhoads reasoned that institutions with “less to lose” are more willing to give credit than highly prestigious campuses like Harvard and MIT. For example, Colorado State University became one of the first universities to offer credit for completing a MOOC (Lewin, 2012) and at present, the University of Arizona is making a full freshman year available via MOOCs in partnership with edX called Global Freshman Academy (edX, 2017).

According to the literature, the difference in institutional behavior is attributed to changes in institutional values and priorities (Rhoads, 2015; Waks, 2016). Decreases in public dollars and increased competition have created an environment that compels institutions to change. This environment did not exist when OER/OCWs were developed.

Institutional Motives and Goals for MOOCs

MOOCs are a relatively new phenomenon, and empirical and conceptual research on them is still emerging. Three studies have examined why higher education has adopted them. Fiona Hollands and Devyani Tirthali (2015) conducted a study on the institutional goals and strategies related to MOOCs. Thus far, it is the most comprehensive study on the underlying goals of institutional innovation. The researchers interviewed leadership at 29 public and private colleges and universities that offer MOOCs. Their findings included six major institutional goals for MOOCs: (a) extending the reach of the institution and access to education; (b) building and maintaining brand; (c) improving economics by lowering costs or increasing revenues; (d) improving educational outcomes for both MOOC participants and on-campus students; (e) innovating in teaching and learning; and (f) conducting research on teaching and learning.

The most common goal was extending reach and access to higher education, with approximately two-thirds of the interviewees citing this as their first goal. The researchers also found that more than creating revenue, institutions wanted to lower costs. Simultaneously, institutions did not want to lose money, so some chose certain providers over others to generate at least enough revenue to offset the cost of course production. For example, Hollands and Tirthali noted that several institutions considered partnering with Canvas instead of edX because edX prohibited institutions from charging for their courses, whereas Canvas did not. In their study on the cost effectiveness of MOOCs, the researchers found that these institutions expended considerable resources to produce a MOOC and thus only well-off institutions would be able to produce them (Hollands & Tirthali, 2014)

In another study on the adoption of MOOCs, DeRousie (2014) examined why institutions adopted MOOCs while using a dataset similar to the one I used in the present study. DeRousie used a discrete time hazard (DTH) model to study the diffusion of MOOCs along with four other innovations (e.g., test optional admissions, the common application, no loan financial aid, and MOOCs). His sample consisted of approximately 1,300 institutions for each of the innovations over a 26-year time period. In his approach, he examined the environmental context, the social network, and the adopters' characteristics to see if any of these attributes uniformly predicted innovation. His analysis on MOOCs included 2 years of data (2012 and 2013) and 81 adopters in total. DeRousie manually collected information on MOOCs by reviewing websites that posted new information about adopters as they were announced, making his data collection somewhat prone to sampling error. He also merged institutional data to IPEDS data. However, IPEDS reports data in academic years (July 1 through June 30) and DeRousie did not distinguish MOOC adoption by academic years. This means that his distribution of the courses over time was

incorrectly recorded, but taking this approach probably did not considerably affect his study results, however, given that his variables were not time-variant and remained stable from year to year.

The results of DeRousie's MOOC analysis were mostly non-significant. The year in which MOOCs was adopted was significant as were institutions that were "most competitive," "highly competitive," and "very competitive" in the Barron's selectivity index. However, no other indicators of his approach were significant. Non-significant findings included other Barron's classifications, geographic comparisons, and Carnegie classifications. DeRousie noted that his findings were limited by having only 2 years of data.

The last study was an annual national survey collected by the Babson Survey Research Group in partnership with the College Board of chief academic officers, from which I. Elaine Allen and Jeff Seaman create an annual report on the nature and extent of online education in higher education. The January 2013 report, which provided responses for the 2012 academic year, was the first survey to provide answers on MOOCs. The survey asked respondents questions about the institutional use of and goals for MOOCs. Some examples of questions included whether institutions planned to adopt MOOCs, whether they were working with providers, whether MOOCs were a sustainable method for offering online courses, and how institutions intended to use MOOCs. They also found that public universities offered more MOOCs than private nonprofit and for-profit colleges. The for-profit colleges had the highest rate of being in the "planning stages" of adopting MOOCs. In addition, large universities (more than 15,000 students) offered more MOOCs than others, and research/doctoral universities offered MOOCs twice as often as non-research/doctoral institutions. The researchers also found

that associate institutions believed they were in the lead to scale their offerings, while research universities believed they were the best prepared to develop innovative new courses.

Over the course of the next 3 years of surveys, the number of MOOC adopters increased while the number of institutions planning to offer them decreased (Allen & Seaman, 2013, 2014, 2015, 2016). The chief academic officers were in general agreement that offering MOOCs provided institutions with important opportunities to learn about online pedagogy, but they also believed offering MOOCs was unsustainable.

The Politics of MOOCs and Open Online Education

Increased openness to online education was evident among key players involved in shaping nonprofit higher education, including policymakers, governing boards, and institutional leaders (Rhoads, 2015). First, state-level legislative bodies and governing boards challenged their respective states' public colleges and universities to make greater use of online education as a cost-savings measure and a way of expanding access. For instance, at least three states (e.g., Florida, Arizona, and California) created task forces to help expand college access through online programs and develop cutting-edge technology instructional design for online programs and student success in these programs (Rhoads, 2015). Florida's Governor Rick Scott signed a bill into law that encouraged the state's K-12 and higher education systems to use massive open online courses (MOOCs) (Rivard, 2013a).

However, the more extensive experimentation occurred in California. Former Senate pro Tempore Darrell Steinberg introduced legislation to create the first statewide system in the nation. California was still reeling from the Great Recession, and the state could not afford to fund the higher education system. Although the California Master Plan guaranteed access to all students, the system could not accommodate these students with their current supply of resources.

Thus, Steinberg introduced SB 520, a bill that proposed using a network of MOOC adopters and other online providers to ease the bottleneck of students into intro-level courses for the California public community college and university system (SB 520, 2013). In support of the bill, he said:

The California Master Plan for Higher Education promised open access to all, yet thousands of students are struggling to complete their degrees and going deeper in college debt because there simply aren't enough classroom seats available in the courses they need. . . . We need to tear down these barriers. We want to lead the nation in melding technology with our great institutions of higher learning. No college student in California should be denied the right to move through their education because they couldn't get a seat for the course they needed. (Steinberg, 2013)

In addition to state-level leaders, national leaders also showed support for increased online education in postsecondary education. For instance, President Obama's Council of Advisors on Science and Technology (PCAST) in 2013 released a report that reinforced the usefulness of MOOCs and online education in general. In the report, PCAST also recommended that the U.S. Department of Education encourage regional accrediting bodies to be more flexible in considering how to meet standards through the use of online education. PCAST also advocated for the federal government to further support competitive extramural grant programs for research and development in the area of online teaching and learning.

Despite growing state-level and national support for MOOCs, institutions continued to push back, especially faculty who were skeptical of greater reliance on online education (Lederman, 2016; Rhoads, 2015; Waks, 2016). Forcing higher education to turn to online education and MOOCs to increase efficiency was often at odds with university values. For example, when SB 520 was introduced, faculty representatives purportedly almost uniformly opposed the measure (Rivard, 2013c; Says, 2013). The faculty warned that California was preemptively preparing to outsource student learning to for-profit companies that had not proved their courses maintained high enough standards of quality (Rivard, 2013a). Faculty also saw the

provision of the new education through for-profit providers as a scheme that promoted further privatization of the system. The University of California's Academic Senate wrote that "clear self-interest of for-profit corporations in promoting the privatization of public higher education through this legislation is dismaying" (Rivard, 2013c). Faculty were also concerned that increasing the use of online education would threaten their autonomy in deciding what to teach (Rhoads, 2015) or undermine other teachers' decisions (Hechinger, 2013). Finally, many feared that offering MOOCs and similar types of innovations as an alternative to face-to-face instruction would mean creating greater inequalities in access to high-quality education (Hechinger, 2013). For instance, where wealthy and academically well-prepared students were more likely to obtain a traditional, high-quality education, underprepared students or nontraditional students would be the likely takers of online education, especially if it is used to lower instructional costs. The research also suggested that underprepared students were actually negatively impacted by online learning, compared to face-to-face instruction (Xu & Jaggars, 2011). Nevertheless, there was some speculation that the universities were more motivated by self-interest and maintaining control over the provision of higher education, even if adopting online learning meant reducing the cost of education (*The Economist*, 2015).

Costs and Associated Problems of Disrupting Higher Education

The cost of disrupting higher education does not come cheaply. For example, to produce one MOOC, Hollands and Tirthali (2014) estimated that campuses spent between \$200,000 and \$325,000. Only elite campuses can manage such an expense without cutting into important funds earmarked for other core activities. Although technology has advanced, the point remains that educating students is challenging and expensive—a point not forgotten by key higher education stakeholders. In an interview with Mark Baldassare, president of the Public Policy Institute of

California, University of California president Janet Napolitano noted that online education is a useful tool, but when done right, it “doesn’t save all that much money, because you still have to have an opportunity for students to interact with either a teaching assistant or an assistant professor at some level” (Rhoads, 2015, p. 89). Napolitano added that if the course was going to be top-quality, it would also require significant investment.

MOOCs have also been widely criticized for their low completion rates. According to a 2013 study by Katy Parr, only 7% of MOOC students completed the courses on average (Jordan, 2015). A more recent study on the Georgia Tech’s MOOC-based Master’s degree in computer science found that 80% of its students completed the program, but they had to apply to the program and were awarded a degree at the end from Georgia Tech (Online Course Report, 2016). These results for Georgia Tech were not reflective of MOOCs overall because MOOCs generally do not offer credit.

Finally, as they currently exist, MOOCs may not be an effective solution for opening access and reducing costs for nontraditional college students. First, according to research from 2016, MOOC learners tended to possess one or more degrees already and fall in the age range of 25-40 years old (Online Course Report, 2016). Thus, these learners were not the target population of students the Obama administration was seeking to expand access to in the 2020 Completion Goal. Further, it is unlikely that MOOCs would be an effective solution for students who have families and work, and are academically underprepared. In 2011, Di Xu and Shanna Jaggars conducted a rigorous quasi-experimental study on the impact of face-to-face versus online education in community college students. They found that students who took online education did worse than students who took the same course in a face-to-face format in terms of course retention and course performance (Xu & Jaggars, 2011). Their findings suggested that

underprepared students may need more face-to-face support than well-prepared students. MOOCs were actually used to replace face-to-face introductory and remedial courses in a partnership between Udacity and San Jose State University in the Spring of 2013. The experiment was abruptly halted when the courses posted pass rates of between 23.8% and 50.5%, which were much lower than their on-campus equivalents (Straumsheim, 2013).

If these concerns were not enough, MOOCs and other disruptive technologies still face the same problems that all online platforms face, specifically epistemological and pedagogical limitations (Rhoads, 2015; Waks, 2016). Rhoads (2015) focused on these two issues at length. First, he noted that there are still many shortcomings in educational research on how knowledge is conceived and how relationships between teachers and students are structured. He contended that when economies of scale are prioritized, as they were with MOOCs, one of the major challenges becomes identifying what knowledge is suitable to be delivered online (Rhoads, 2015; Walsh, 2011). Accordingly, when MOOCs became popular in 2012, advocates were primarily concerned with increasing access and scalability while also tying MOOCs to credits. In order to make them scalable to the masses, many of the first MOOCs treated knowledge as static—delivered facts and bit forms of information. Delivering information in this way was not what Siemens and the other early MOOC designers imagined: courses in which students were connected and learning through social learning networks, not through static lecture formats. But in the MOOC format used for the masses, Rhoads posited that learning and knowledge were tied to a more “foundationalist” view of knowledge, where opportunities to engage in meaningful forms of social learning were inconsequential or nonexistent.

Rhoads (2015) was also concerned with pedagogy when creating courses to achieve economies of scale. Whereas pedagogy focuses on the delivery mechanisms of conveying knowledge, Rhoads found that in MOOCs, these mechanisms were generally one-directional (p. 99). The type of delivery structure, he argued, did not encourage the development of critical thinking in students, but rather perpetuated the traditional delivery of information from teacher to student, where students' minds remain mostly passive.

In Review

The accountability movement was motivated in large part to massify higher education with less expense, but the repercussions have led to financial hardship for higher education which, in turn, has created critical issues of affordability and value for students. In order to correct for those consequences, policymakers have turned to economic competition to induce institutions to adopt disruptive innovations that would lower their costs and increase affordability for students. At the same time, few studies exist on whether economic competition is effective in incentivizing systematic disruptive innovation.

This literature review examined the few studies that have investigated the adoption of disruptive innovation. They have suggested that some institutions are driven by economic competition, while others are driven to add to the research on teaching and learning. While they are not necessarily at odds with each other, the research on nonprofit versus for-profit OER and OCW providers has suggested they might be. More information on what causes the systematic uptake of disruptive innovation is needed.

The state of the research on MOOCs and similar types of disruptive innovations is underdeveloped. The existing research was limited by amount and breadth of data. The studies offer some preliminary analysis of what mechanisms lead to the adoption of a disruptive

innovation, but the system is treated as a monolithic group of adopters or non-adopters, paying little attention to the institutional characteristics and mechanisms of diffusion that distinguish not only adopters from non-adopters but also adopters from each other. Capturing the ways disruptive innovation takes place across the system matters because the system is extremely heterogeneous (Meyer & Rowan, 2006). Some researchers have argued that publics are less likely to innovate than private nonprofits because they are buffered from market forces by state subsidies (Brewer & Tierney, 2010; Kezar, 2014; Levine, 1980), while others have argued that there is no longer a difference between the two types (Slaughter & Rhoades, 2004). Still others have reasoned that only the for-profit or lower-tier institutions are likely to innovate because they are dependent on filling seats to generate revenue (Brewer et al., 2001; Christensen & Eyring, 2011). It is urgent to understand this phenomenon if states desire increased efficiency and innovation from higher education beyond the Obama administration.

In sum, for policymakers to induce the systematic adoption of innovation across institutions, understanding how this can take place is key. The rapid adoption of MOOCs provides a unique opportunity for examining the system-wide institutional uptake of a disruptive innovation. In the next section, I lay out the theoretical and analytical framework for investigating the systematic adoption of a disruptive innovation in U.S. higher education.

Theoretical Framework

Incentivizing and achieving effective institutional innovation looms large on government and higher education agendas. Although critics of traditional higher education have bemoaned the lack of innovation, the research on how systematic innovation is achieved is limited (Baum et al., 2013; Brewer & Tierney, 2010; Diamond, 2006). In this research, I investigated the relationship between competing incentives and the systematic adoption of a disruptive

innovation to shed light on the process of and theory related to systematic disruptive innovation in higher education. While the theories on the diffusion of innovation are well developed, theories on the diffusion of disruptive innovation are not. From a theoretical position, therefore, my specific aim was to examine the extent to which theories explaining the diffusion of an innovation can be used to explain the diffusion of disruptive innovation in higher education.

Very limited empirical and conceptual research exists on systematic disruptive innovation. The most well-known theory was formulated by Clayton Christensen, the Harvard business professor who proposed the *theory of disruptive innovation* in 1995 (Bower & Christensen, 1995). According to Christensen et al. (2011):

disruptive innovation is the process by which a sector that has previously served only a limited few because its products and services were complicated, expensive, and inaccessible, is transformed into one whose products and services are simple, affordable, and convenient and serves many no matter their wealth or expertise. (p. 2)

The product or service takes root initially in simple applications at the bottom of a market and then relentlessly moves up market, eventually displacing established competitors (Christensen Institute, 2017). In education, this innovation is cheaper and more accessible to nontraditional students. Ultimately, the purpose of a disruptive innovation is to save students time and money (Christensen & Horn, 2013).

The early adoption of MOOCs was viewed through this light of disruptive innovation (Christensen & Weise, 2014; Yuan & Powell, 2013). However, the theory failed to hold up. According to Horn (2013), a member of the Christensen Institute that studies disruptive innovation, the expansion of MOOCs bore many markers of disruption when narrowly defined, but they lacked a clear business model that enabled their disruptive value proposition to be sustainable and able to move up-market over time. According to Christensen and Weise (2014), because MOOCs were massive and open, they could not command a paying market and were

therefore non sustainable from the perspective of the original Christensen theory of disruptive innovation. Moreover, the value proposition of MOOCs was that they were courses provided by faculty from traditional colleges and universities as opposed to alternative providers. Thus, Horn (2013) said that if the cache of MOOCs relied on traditional college and university faculty participation, it was unlikely that the university would use online learning to move up-market in terms of teaching and learning.

If that theoretical model was not a good predictor of the institutional adoption of MOOCs, then what does explain their systematic adoption? For this, I turned to policy diffusion literature to approach the systematic adoption of MOOCs. Because no framework at present exists to explain disruptive innovation in higher education, I invoked the internal determinants and diffusion model because it has been well-tested and has endured over the years (Berry & Berry, 1990, 2014; Berry & Baybeck, 2005; Cohen-Vogel, Ingle, Levine, & Spence, 2008; Doyle, McLendon, & Hearn, 2010; Shipan & Volden, 2006; Walker, 1969). Political scientists have found two main principles that drive the adoption of a new program or policy: *internal determinants* and *diffusion* (Berry & Berry, 1990, 2014). Internal determinants are political, economic, and social factors that compel an organization to innovate. Diffusion of an innovation occurs when it is “communicated through certain channels over time among the members of a social system” (Rogers, 1983, p. 5). Mechanisms of diffusion are therefore interorganizational. Examples of common mechanisms of diffusion are *normative pressures*, which stems primarily from professionalization); *mimetic*, where imitation is encouraged because the environment is characterized by uncertainty, goals are ambiguous, or organizational technologies are poorly understood; *coercive*, where formal and informal pressures exerted by a more powerful organization encourage institutions to conform; and *competition*, where an organization adopts

an innovation to achieve an economic advantage over other organizations or to prevent other organizations from secreting an economic advantage over it (Berry & Berry, 2014; DiMaggio & Powell, 1983). Berry and Berry (2014) have argued that internal determinants and the mechanisms of diffusion (e.g., competition) can and should be considered simultaneously to explain the adoption of innovation. They also noted the type of institutions that adopt an innovation change over time (Berry & Berry, 2014; Cyert & March, 1963; Rogers, 1983).

Therefore, in applying this theory of diffusion to the expansion of MOOCs in higher education, I suggest that at least two mechanisms of diffusion drive the systematic adoption of MOOCs. The first is *economic competition*. While there is significant pressure to expand sources of market competition for higher education in order to induce change, not much has been documented on whether this type of pressure engenders systematic disruptive innovation. Nevertheless, there is growing evidence that higher education is in fact increasingly responsive to market forces (Ehrenberg, 2006; Slaughter & Rhoades, 2004; Zusman, 2005). Given the policy focus and evidence of institutional adoption of more market-like behavior, I use the *theory of academic capitalism* (Slaughter & Leslie, 1997; Slaughter & Rhoades, 1996) to frame *economic competition* as the driver of MOOCs. However, because higher education, at the same time, is traditionally a group of prestige maximizers—for which there is still substantial evidence that they emulate and chase prestige, I counter academic capitalism with the second mechanism of diffusion, *competition for prestige* (Brewer et al., 2001; Christensen & Eyring, 2011).

Academic Capitalism

The term *academic capitalism* was first coined in 1997 by Sheila Slaughter and Larry Leslie to describe the processes colleges and universities used to integrate with the “new” knowledge-based economy. The definition of academic capitalism is the involvement of colleges

and faculty in market-like behaviors. Initially, academic capitalism helped to rationalize institutional efforts to find new sources of revenue when state and federal sources dried up. For instance, universities would accept commissions from industry for applied research rather than only work on “pure” research in order to fund themselves (Deem, 2001). Once professors pursued private sector funding, they became state-subsidized entrepreneurs, even if they were still technically public sector actors (Slaughter & Leslie, 1997, p. 9).

Over time, and once higher education’s role in the new economy had expanded, Slaughter and Rhoades (2004) redefined academic capitalism. They argued that the for-profit-oriented activities of higher education had actually become embedded within the university. Specifically, university actors had become interested in developing their own capacity to market products to the outside while remaining connected to the home institution and conventional academic structures. Consequently, the new definition of academic capitalism became the institutional *pursuit* of market and market-like activities to generate external revenues (p. 11). In essence, just as the state had shifted away from a welfare function toward a production function, higher education had also undergone a transformation from public good knowledge/learning regime to an academic capitalist knowledge/learning regime (p. 28).

Academic capitalism, according to Slaughter and Rhoades (2004), identifies groups of actors who use state resources to do the following: (a) create new circuits of knowledge that link higher education institutions to the new economy; (b) create interstitial organizations that bring the corporate sector inside the university; (c) develop new networks that are intermediates between the public and private sector; and (d) expand managerial capacity to supervise new flows of external resources, investments in research, and investments in infrastructure to market products and services to students. New circuits of knowledge appear when knowledge is more

accountable to bodies other than scholarly, scientific, or professional networks. For example, outside organizations and publications such as the *U.S. News and World Report* rate college and university performance in order to judge their worth to the student/parent consumer. New circuits of knowledge could also be formed when university graduate degree-holders work in industry instead of academia. New interstitial organizations could include profit centers, trademark licensing, and fundraising offices. The key is that interstitial organizations must generally be embedded in the campus. Networks that act as intermediaries between the public and private sectors could be organizations like Educause or the League for Innovation. Extended managerial capacity is the growth in the number of managers who can oversee interstitial organizational emergence and, to an extent, intermediating networks. While Slaughter and Rhoades focused primarily on patents and copyrights to exemplify extended managerial capacity, they posited that distance education centers, economic development offices, foundations, and other organizations can also be investigated for expanding managerial capacity. The role of these managers is to negotiate with the private to commercialize aspects of the university (e.g., teaching materials, curriculum, videos, etc.).

Ultimately, Slaughter and Rhoades suggested that these different avenues of building links to the market exemplify how higher education uses their core educational, research, and service functions to *generate revenue*. To explain change in higher education, I argue that the more evidence of expanding into the market through these different avenues (e.g., working with the private sector, expanding into the student market via distance education, reducing costs by hiring adjuncts, or hiring more managers to create efficiencies on campus and in the market), the stronger the hold of the academic capitalist regime and the greater the motivation to generate revenue in the academic setting. Thus, from one perspective, I sought to examine the extent to

which MOOC adoption is a product of institutional competition for revenue, assuming that conditions of academic capitalism apply. The other perspective is rooted in an institutional focus on competition for prestige.

Prestige Acquisition

The pursuit of prestige is another powerful instrument of institutional change, according to the higher education literature (Brewer et al., 2001; Christensen & Eyring, 2011; Heller, 2001; Volkwein & Sweitzer, 2006). Brewer et al. (2001) conducted site visits to 26 different institutions and interviewed more than 200 administrators, students, and faculty in order to understand institutional strategy; it is one of the most thorough studies I have found on the pursuit of prestige. The researchers argued that identifying which factors influence higher education behavior is more complicated than understanding what motivates for-profit firms. That is, while for-profit firms are motivated by maximizing returns, nonprofit higher education cannot maximize profits since their nonprofit charter prohibits it, making their incentive less evident (Brewer et al., 2001, p. 20). Nonetheless, there is wide consensus that institutions, if not pursuing revenue, are pursuing prestige (Christensen & Eyring, 2011; Selingo, 2013). Prestige confers certain advantages, namely easier flow of research dollars, donor support, and more demand than supply for student seats (Brewer et al., 2001). As they acquire more research dollars and are able to turn down more students, then the institution, relative to its peers, becomes more prestigious.

According to Brewer et al. (2001), the most likely institutions to experiment are those *without* high levels of prestige. These institutions are not high-capacity research institutions nor are they highly selective. Whereas the most prestigious institutions (as measured by research dollars, selectivity, and notable sports programs) tend to make only incremental changes to maintain their reputation, such as expanding their recruitment networks to find even more

competitive students, institutions that are not selective and without substantial research dollars are more likely to experiment and be innovative in terms of educational delivery. Less prestigious institutions will experiment to either propel them to a position of national or regional prominence or help them cater to a nontraditional student population (pp. 42-43). If the driving currency in higher education were prestige acquisition, then according to Brewer et al.'s findings, the most likely candidates to innovate would be institutions that are the bottom and just outside the most selective schools—specifically schools with no or limited research and schools with no or little selectivity.

It is difficult to reconcile the fact that Brewer et al. (2001) noted how the most prestigious institutions were least likely to be innovative in educational delivery (p. 66), but the pioneers of MOOCs (e.g., Harvard, MIT, and Stanford) were indisputably among the most prestigious in the world. They did argue that internal competition for prestige compels elite institutions to perform better than their competitors, which leads them to invest in new ideas to raise industry standards continuously. But they also repeatedly suggested that innovations that expand access to students are not part of the character profile of the most prestigious institutions because the selectivity of their student population sustains their prestige. Perhaps between the time that Brewer et al. conducted their study and the time that MOOCs emerged, political and economic pressures on elite institutions had built to the point of requiring these institutions to be pedagogical innovators. Alternatively, the two points may also be reconciled in that prestigious institutions, in order to remain being seen as pedagogical leaders, are compelled to adopt MOOCs. However, this does not mean that these institutions wish to use MOOCs to expand access to higher education or widen their own enrollments without differentiating those users from their

traditional users. For example, UC Berkeley offers UCB Extension as does Harvard with Harvard Extension.

The bottom line is that research on what incentivizes the systematic adoption of a disruptive innovation in higher education is still rudimentary. This can be partly attributed to the complex political and economic climate that envelops higher education. In the remainder of this dissertation, I investigate the extent to which prestige acquisition and economic competition influence the adoption of MOOCs when controlling for other confounding factors, whether these incentives change over time, and for which groups of institutions these incentives are most effective at inducing institutional change.

Internal Determinants

The policy diffusion model proposes a model for understanding why a decision-making body (e.g., jurisdiction or college or university) adopts a new innovation (Berry & Berry, 2014). The model not only requires the inclusion of mechanisms of diffusion as described above, but it also requires the inclusion of *internal determinants*, which are the internal characteristics causing a decision-making body to adopt a new program or policy. Internal determinants are the attributes of an institution that induce innovativeness at the institutional level; that is, internal determinants are not dependent on interactions with other organizations as are the mechanisms of diffusion. Many innovations cost money or involve financial risks for organizations that adopt them. Hence, greater income and wealth provide the decision-making body (e.g., individual, jurisdiction, or college and university in this case) with the resources necessary to absorb these costs. Therefore, larger organizations and those with greater levels of “slack” resources are assumed to be more innovative than smaller organizations and those with fewer resources (Berry & Berry, 2014; Cyert & March, 1963; Rogers, 1983; Walker, 1969). In comparison, institutions

that do not have these slack resources or benefits of size to absorb risk are less likely to innovate (Berry & Berry, 2014; Mohr, 1969). The inclusion of these internal characteristics in the model sheds light on the institutional motivation to innovate, the obstacles to innovation, and whether the organization has the resources to overcome the obstacles to innovation (Berry & Berry, 2014; Mohr, 1969). Internal determinants are discussed in the next chapter.

Chapter 3: Methods

Despite growing government and private sector interest in higher education innovation, little empirical and conceptual work exists on what drives disruptive innovation in higher education. The present study sought to fill this void in research. The prevailing literature has argued that institutions change either to pursue profits or to pursue prestige. In this study, I used an original dataset to compare prestige-seeking versus economic-competition frameworks to investigate the drivers of disruptive technological innovation in higher education.

The questions asked in this study were:

1. When is MOOC adoption most likely? How does prestige-seeking behavior compared to economic competition influence the adoption of MOOCs?
2. Does partnership with a for-profit versus nonprofit provider differ by prestige-seeking behavior or economic competition? Do these partnerships change over time?
3. To what extent does a typology of institutional innovators based on prestige-seeking behavior and economic competition exist? To what extent does this typology of innovators relate to MOOC adoption? How does the adoption of innovation by institutional subgroup vary over time?

Population and Data Collection

The data for this study came from two sources. Institutional data were provided by the Integrated Postsecondary Education Data System (IPEDS), which is sponsored by the NCES under the U.S. Department of Education (IPEDS, 2016). IPEDS is the primary source of annual panel data for accredited postsecondary institutions that are eligible for Title IV financial aid. The IPEDS survey components used in the study included: Admissions, Finance, Completions, Human Resources, and Institutional Characteristics for academic years (AY) 2011-12 through

2014-15. Data were cleaned in Stata 14.0 and converted into panel format so that longitudinal data analysis could be conducted.

The second source of data was a website named Class Central (Class Central, 2016). To my knowledge, it was and remains the largest aggregator of MOOC data. The website provides MOOC characteristics, including the course name, course description, course subject, dates the course was offered, course instructor, length of course, university or college that produced the course, and name of the technical platform provider (such as Coursera, edX, canvas.net, etc.), among other information. I used the tool called *import.io* (Import.io via www.import.io, 2016) to scrape the website's hundreds of pages to export the data into a useable format. After I successfully downloaded historical data, I cleaned these data using Stata.

I validated the data in two ways. I interviewed the founder and CEO of Class Central, Dhawal Shah, to learn how the company collected its data and to verify that the likelihood of missing any MOOC data was low (e.g., to confirm that these data collection strategies had been in place since the first instance of MOOCs). I also sampled the data output from Class Central and compared it to the output of provider websites, and I found no missing data. From this interview, I learned that Class Central uses a very advanced crawler to collect data from the existing MOOC provider websites. Class Central queries websites of providers such as Coursera and edX several times per day to collect any new data. Any new courses are then added to the centralized database at Class Central.

After completing data collection and data cleaning, I matched IPEDS data and Class Central data using institution names to create a new dataset that has never before been analyzed. Then, I adapted the format of my data to fit the requirements of the three separate analyses. For example, as will be discussed in more detail below, the first question utilizes long-format panel

data and the last question utilizes both long-format panel data and wide-format cross-sectional data. The details of each different data structure will be discussed within each of the relevant empirical strategies below.

Sample

Although my parent dataset included the universe of IPEDS colleges and universities, I only examined 4-year, nonprofit private and Title IV public colleges and universities. The literature has asserted that 4-year universities are in dire need of innovation to cut costs and better serve student needs (Bowen, 2015; Carey, 2015; Christensen & Eyring, 2011). This study therefore focused on the adoption of MOOCs as an example of a disruptive innovation in 4-year, public and private nonprofit universities across AY 2011-12 through 2014-15. This means I excluded institutions that had no undergraduate enrollment (e.g. the University of California at San Francisco), since they do not cater to the typical student. I also excluded community colleges for several reasons. They are not recipients of large research federal or private research grants and are not selective. Therefore, examining whether these institutions are driven by prestige or economic competition would be a moot point in the current framework in which I defined prestige as the amount of research conducted by an institution. While community colleges may still vie for status and revenue generation, comparing their quests for status with 4-year institutions would have introduced different variables and conditions that I could not control for in the present study. Community colleges are also missing many data, particularly enrollment data. Since a large portion of my analyses were done using descriptive statistics and not regression, I could not control for the differences between community colleges and 4-year institutions. This would ultimately have biased my errors and estimates, and so I excluded them. A study on the motivation of community colleges should be done separately.

Of the four-year institutions eligible to fit within my study population, there were 2,509 four-year public and private, non-profit institutions. My final analytic sample included 1,470 institutions. The reduction in data was due to employment of listwise regression for missing data. How to handle missing data in longitudinal studies is a widely debated topic (Allison, 2000; Allison, 2002; Schlomer, Bauman, & Card, 2010; Wothke, 2000). Because mean imputation is ill advised for IPEDS data (NCES, 2017b),¹ I employed listwise deletion for institutions that were missing data. This means that I eliminated all cases that had *any* missing data. I excluded from the sample colleges that that were missing one or more years of data. Table D1 in the Appendix shows the overall statistics for missing data. About 1% of these were missing at least 1 of the 4 years of data. About 3% of institutions were missing data for number of managers, and almost 7% of institutions were missing information on employment of adjuncts. About 7% of institutions were missing financial data (e.g. cash flow, end of year endowment, and net tuition). For both certificate programs and distance education programs, a little less than 2% of institutions were missing these data. The biggest source of missing data came from admissions selectivity. Approximately 32% of the colleges were missing admissions data. In total, my dataset lost a little more than 40 percent of institutions (see Appendix D).

Table D2 in Appendix D shows that institutions deleted from the analysis differed from

¹ Mean imputation, according to NCES, is when the mean value is used to “fill in” the missing value. There can be a within-class or an overall mean value imputation. The problem with this method is that it can only provide unbiased estimates for means and total if the missing values meet the strong assumption of missing completely at random (MCAR). This procedure then creates a spike at the mean and distorts the distribution of the existing multivariate relationships in the data. According to Little and Rubin (1987), the distortion of the distribution is especially problematic when the tails of the distribution or the standard errors of the estimates are the focus of the study. In my study, because MOOC adoption is a rare event, many of my cases were on the tails of the distribution. Thus, I elected to not use mean imputation.

those that remained in several important respects. Deleted institutions were more likely to be part of the Religious/Other group (e.g. faith-based, specialty or tribal schools). For instance, the deleted group contained 70% of institutions from the Religious/Other group compared to 10% for the group that remained ($p < 0.001$). They were also less selective (e.g. 27% compared to 36%, $p < 0.001$). Deleted institutions were more dependent on management (14% compared to 11%, $p < 0.001$), and on adjunct faculty (26% compared to 16%, $p < 0.001$). They also offered about one fewer distance ($p < 0.001$) and certification program ($p < 0.01$) compared to the group that remained in the study. Deleted institutions comprised more public institutions, on average, compared to institutions that remained in the study (e.g. 54% compared to 29%, $p < 0.001$). Deleted institutions were also more resource constrained as evidenced by lower cash flow and smaller endowments ($p < 0.001$). For instance, deleted institutions had almost 8 times smaller endowments than institutions that remained in the study. Deleted institutions reported significantly smaller enrollments than institutions in the study (e.g. approximately 2400 compared to 7000 students, respectively, $p < 0.001$). My findings are thus not generalizable to all institutions, but rather to institutions that are not faith-based, tribal, or specialty schools and which have more selective admissions criteria, and more robust enrollments and financial resources.

Measures

Dependent Variables

I examined three different outcomes in this study: MOOC adoption (Section 1), partnership with a for-profit or nonprofit provider (Section 2), and a Latent Class Analysis (LCA) categorical outcome for institutional innovators (Section 3). I discuss each in turn.

MOOC adoption. In question 1, I examined the likelihood of adopting a MOOC from

AY 2011-12 to AY 2014-15. Adoption is defined as offering a MOOC, a free online college-level course over the Internet, for the first time. It is a binary indicator variable (1 = adopted, 0 = did not adopt). Since I was examining the relationship between institutional mechanisms of innovation and the likelihood of adopting MOOCs, whole-state systems that offered MOOCs were not included, but single-state institutions that offered MOOCs were included. A state system is an organizational body that includes multiple public higher education institutions, and a board of regents or some centralized state-level governing board typically governs it. Some systems adopted MOOCs and implemented them across multiple institutions in the system. For example, the State University of New York System, the University of Houston System, the University of Colorado System, and the University System of Georgia all adopted at least one MOOC. But the factors that led to the adoption of MOOCs for the system were likely different and incomparable to those that led to institution-level adoption. Additionally, the financial reporting for systems is aggregated institutional data that would bias the individual, institutional-level data.

MOOC adoption was measured by first launch of a course to the public during any one of the four academic years, where adoption is tied to the date the course was first offered. The MOOC data were cleaned so that any one course that was launched from June 30 of the preceding year to July 31 of the following year was included in the same academic year. For example, if a course launched in September 2012 or January of 2013, both adoptions would be recorded as taking place in AY 2012-13. Most institutions offered at least one additional MOOC after their first launch; I used only the first adoption to isolate the mechanism responsible for changing states (e.g., from a non-disruptive innovator to a disruptive innovator). For example, Dartmouth College offered its first MOOC in AY 2013-14 in environmental science and then

another course in engineering in AY 2014-15 (Author's research). I only used data for AY 2013-14 in which Dartmouth adopted its first MOOC to determine drivers of innovation. Additional adoptions of MOOCs would be non-informative for the purpose of understanding what triggered disruptive innovation.

Choice of MOOC provider. Question 2 investigated the difference in institutional characteristics associated with innovation and partnership with for-profit versus nonprofit providers. The outcome variable for this question was which provider was chosen, rather than the MOOC adoption used in the first question. I used partnerships with a for-profit provider as an indicator of university or college intention to generate a profit. At the time of data collection, 14 providers were based in the U.S., and of these, only 11 partnered with the universities in my sample (Table 1). These 11 providers included five nonprofit and six for-profit providers. I identified whether each of these providers was for-profit compared to nonprofit through a manual website search.

In this study, I only used the provider of the first MOOC that each institution launched. Some institutions partnered with multiple providers over time, but identifying the trends beyond the initial partnership would have been non-informative for this study. Subsequent partnerships may inform policy in terms of learning and to some extent intent, but it is not informative for understanding what catalyzed change initially.

Table 1. Adoption by For-profit and Nonprofit Providers

Provider	Non-profit Provider	For-profit Provider
Canvas.net	0	34
Coursera	0	37
Independent	8	0
Janux	1	0
Kadenze	0	1
MOOC-ED	1	0
MRUniversity	1	0
Open Education by Blackboard	0	21
Udacity	0	1
Udemy	0	1
edX	16	0
Total	27	95

LCA categorical variable. A latent class analysis (LCA) was run for question 3. The method of LCA is discussed in more detail below, but the outcome variable for this question was the latent subgroup of institutional innovators labeled “Latent Classes C” (see Figure 1 later in this chapter). This output variable was constructed from the independent variables described below.

Independent Variables

This dissertation posited two drivers of disruptive innovation: competition for prestige and economic competition, which is the institution’s desire to pursue profit. This section describes the variables used to indicate institutional traits of prestige-seeking and economic competition. These variables were used for all three sections of findings. In addition to my main variables of interest, I also included a description of additional institutional capacity variables, which have been shown in the literature to affect innovative behavior. Indicators of prestige-seeking behavior are reported in Table 2, indicators of economic competition are reported in Table 3, and indicators of institutional capacity are reported in Table 4.

Indicators of prestige-seeking behavior. Higher education is a system of prestige

maximizers (Brewer et al., 2001; Clark, 1983; Slaughter & Rhoades, 2004; Volkwein & Sweitzer, 2006). According to Clark (1983), reputation is the main commodity of exchange for higher education, and relative prestige not only guides the consumer and workers but also guides institutions. Prestige is difficult to measure since it is not a tangible benefit, but it is usually associated with high student quality and high research capacity (Brewer et al., 2001). For institutions with a research emphasis, sponsorship of research provides a major opportunity to build prestige. According to Brewer et al. (2001), attracting research faculty, building research facilities, and operating graduate education programs are all expensive investments that ultimately enable the institution to compete for research sponsorship from the government or private sponsors (p. 32). There are generally prestigious institutions (e.g., high student quality and high research capacity) and prestige-seeking institutions (e.g., lower quality students and lower research capacity). Institutions that are prestige-seeking are more likely to innovate according to some research (Brewer et al., 2001; Brewer & Tierney, 2010). Researchers use various indicators of prestige including student quality (the average SAT or ACT scores of entering students, the restricted Barron's Selectivity Index, admissions selectivity), the amount of revenue generated from private gifts and donations, or the amount of federal research dollars an institution receives (Brewer et al., 2001; Marginson, 2006; Marginson & Van der Wende, 2007; Volkwein, 1987).

I used *admissions selectivity* as one measure of student quality dimension of institutional prestige (Table 2). Scholastic Aptitude Test (SAT) and American College Testing (ACT) scores are not universally accepted by all colleges. Barron's Selectivity Index is often used, but it requires a restricted data license and requires oversight of how the data can be used and published. Admissions selectivity was calculated by using the total number of admissions over

total number of applicants and then reverse-coded so that the lowest number represented the least selective and the highest number represented the most selective. Using this variable presents two limitations. First, 30% of institutions were missing admissions data, which caused me to lose valuable information and power once I eliminated these data using listwise deletion. Additionally, selectivity can be a very inflated measure of student competitiveness. For instance, when the Common Application went online in 1998, students could apply to college much more easily. Students were simply applying to more schools because they could. As the number of applications went up but the seat number remained the same, many institutions experienced a surge in their selectivity (Edmonds, 2013). This did not necessarily mean that the caliber of their student changed or that the school became more selective, but merely that higher numbers of less competitive students were applying to college because they could. They were then rejected, creating a lower admission rate (or higher rejection rate).

In addition to student quality, researchers also take into account an institution's research capacity to measure prestige (Brewer et al., 2001; Volkwein & Sweitzer, 2006). Research capacity differentiates prestigious universities from the rest of the sample. Research institutions have increased control and bargaining power. They also have the ability to attract more federal and state support, giving them even more bargaining power (Levine, 1980). In order to capture prestige garnered from the institution's research capacity, I used the 2010 Carnegie Classification framework to demonstrate research orientation (Carnegie Classification of Institutions of Higher Education, 2017). The Carnegie Classification is a widely used framework for classifying colleges and universities in the United States, and is especially useful for researchers who wish to control for and observe the variation in higher education institutions. I used the 2010 Basic Classification Structure to create variables for my institutions. This category

included separate codes for research institutions (R1, R2, R3 Doctoral Universities); Master's Colleges and Universities (larger, medium, and smaller programs); Baccalaureate Colleges (Arts & Science Focus and Diverse Fields); Baccalaureate/Associates Colleges, and so on. Because my study focused exclusively on 4-year adoption of disruptive innovations, I did not include any Associates colleges. I recoded the Carnegie Classification into Research Institutions, Masters, Bachelors, and Other/Religious.

Using the Carnegie Classification may result in an overly simplistic designation of which institution is already prestigious, prestige-seeking, and not prestigious. According to my study, institutions that were both highly selective and had high research capacity were considered prestigious. Institutions that did not have a high research capacity were not considered prestigious in this study. For example, a small liberal arts college that is highly selective, such as Haverford in Pennsylvania, is probably not persuaded by the same drivers of change as UC Berkeley. Many would still consider Haverford a highly prestigious institution that caters to high-achieving students who want a small college environment. Nonetheless, in the present study, this institution would be considered less prestigious than UC Berkeley, which is both highly selective and research-intensive. Additionally, within the research university group, there is still much heterogeneity in terms of research capacity. For example, Harvard University receives more research funding in terms of grants and contracts than the University of Georgia at Athens, but both are high-capacity research institutions. The selectivity index that I employed, then, helped to account for the differences in these institutional levels of prestige.

Table 2. Indicators of Prestige

Variable Name	Description	Indicator of Prestige
<i>Carnegie</i>		
Research university (%)	Includes institutions that awarded at least 20 research/scholarship doctoral degrees during the update year. Does not include professional practice doctoral-level degrees, such as the JD, MD, PharmD, DPT, etc. Highest level of distinction.	High research capacity is an indicator of high prestige.
Masters university (%)	Generally includes institutions that awarded at least 50 master's degrees and fewer than 20 doctoral degrees during the update year.	Limited research capacity is an indicator of lower prestige.
Bachelors university (%)	Includes institutions where baccalaureate or higher degrees represent at least 50 percent of all degrees but where fewer than 50 master's degrees or 20 doctoral degrees were awarded during the update year.	No research capacity is an indicator of lower prestige.
Religious/Other (%)	Institutions with a special focus/concentration.	No research capacity is an indicator of lower prestige.
Admissions selectivity	Percent of students that the institutions reject each year. It is calculated by dividing the total number of admits out of the total applicants. Then the value is reverse coded to get a ranking from lowest to highest for selectivity.	Indicator of admissions selectivity, where a higher value indicates a more prestigious institution.

Indicators of economic competition. The other driver of change posited in this study was economic competition. My measures of economic competition were grounded in Slaughter and Rhoades' (2004) *theory of academic capitalism*, which is the involvement of colleges and faculty in market-like behaviors in the *new economy*. The new economy is the post-industrial economy in which knowledge is treated less as a public good than as a commodity to be capitalized on in profit-oriented activities (Slaughter & Rhoades, 2004). This theory includes several mechanisms by which colleges and universities expand into the market and compete for profit: *evolving circuits of knowledge*, *interstitial organizations*, *extended managerial capacity*, and *market-behaviors and professional strategies* that provide paths for the university or college to connect to the new economy. *Expanding circuits of knowledge* are characterized by the university operating in the private sector (e.g., academics in industry). Second, *interstitial*

organizations are the emergence of “interstices of established colleges and universities to manage new activities related to the generation of external revenues” (Slaughter & Rhoades, 2004, p. 23). These interstitial organizations are perceived as profit centers. Third is the *extended managerial capacity*, which arose from the need to manage the growth of the interstitial organizations and expanding circuits of knowledge. This means that college leaders who were trying to position their colleges to be more competitive in the market place approved the growth of mid-level and senior-level management to increase the institution’s capacity to engage the market (p. 25). The fourth and fifth attributes of their theory are *market behaviors and professional strategies*. These are indicators of how colleges engage in an array of miscellaneous market and market-like behaviors and professional strategies to monetize activities.

After extensive data cleaning and analysis for variable selection to ensure model parsimony, I ultimately used the following variables as proxies for the economic competition argument proposed by Slaughter and Rhoades: percent of total revenue from private contracts and grants (*% Pvt Grants and Contracts*); percent of staff that is either mid- or senior-level management (*% Management*); percent of instructional staff that are adjunct faculty (*% Adjunct*); the total number of distance programs a school offered (*Distance education programs*); and the total number of certificates (*Certificate programs*).

Table 3 reports the terms, descriptions, and what specifically each of the indicators was used for in this study. Each of the variables allows for a slightly different indication of the way the institutions engage in economic competition in the new economy. For example, institutions might focus on competing for more of the nontraditional student population through the increase of distance education programs and certificate programs (Allen & Seaman, 2014; Bok, 2009; Marginson, 2006; Waks, 2016) or they might use more adjuncts or “contingent” faculty to cut

costs where cutting costs makes an institution more efficient and market-like (Christensen & Eyring, 2011; Waks, 2016; Zusman, 2005) or increased hiring of managers to play a more active role in shaping the curriculum, making the campus more of a competitive marketplace, increasing efficiencies, and overseeing expansion into the new economy (Rhoades & Slaughter, 2004; Slaughter & Rhoades, 2004).

Finance and staffing variables were created as a percent in order to assess university intent and penetration into the new economy. For example, the percent of mid- and senior-level business staff out of total staff provides an estimate for how much emphasis the university is putting on building capacity to oversee business development. If tuition formed a larger percent of total revenue for one institution compared to the percent at another institution, inferences can be drawn about how dependent that institution is on tuition compared to the other. If I had only used dollar amounts, I would not have been able to compare relative dependency. If I had only used the numbers as continuous variables, then the estimates would just be based on absolute size and would only show university or college capacity rather than intention. Hence, except for distance and certificate courses, the rest all ranged from 0-100%.

Table 3. Indicators of Economic Competition

Variable Name	Description	Indicator of Economic Competition
Private contracts/ grants as % of total rev	This is the percent of core revenues that come from private grants and contracts. Examples are research projects and similar.	This is an indicator of the institution's interest in expanding into private sector research for the purposes of generating income. A higher percentage of revenue from private contracts and grants indicates a higher degree of economic competitiveness.
Management as % of staff	This is the proportion FTE executive administrators, management, and business and financial personnel out of total staff. Collectively, I refer to this group as "management."	The dependence on management is an indicator of how much the campus values expanding higher education's capacity into the new economy. It also indicates the extent to which a campus uses a managerial approach in its operations. A higher percentage of managers indicates a higher degree of economic competitiveness.
Adjunct instructors as % of instructors	This is the proportion of FTE adjuncts out of the total instructional staff.	The percent of adjuncts is an indicator of how price-sensitive the institution is and how much it values the bottom line. Full-time faculty are more expensive than contingent faculty, and these positions are becoming increasingly rarer as institutions shed expenses to increase competitiveness (Waks, 2016). A higher percentage of adjunct faculty indicates a higher degree of economic competitiveness.
Total distance programs	This is the number of distance education programs offered. These are programs for which all the required coursework for program completion is able to be completed via distance education courses.	The number of distance education programs is an indicator of how extensive the institution is with catering to the nontraditional student market. With the adoption of new information and instructional technologies, distance education allows institutions to access new student markets – especially students who are able to pay (Slaughter & Rhoades, 2004, p. 44). Distance education also means institutions can copyright new educational material, which allows the institution new sources of revenue. More distance education courses is evidence of more economic competitiveness.
Total certificate programs	This is total number of on-campus certificate programs offered.	The number of certificates is an indicator of expanding reach to the nontraditional student markets. Certificates offer a short-term, skills-specific credential. They cater to the new nontraditional student that is looking to upskill or reskill (Waks, 2016). More certificates programs is evidence of more economic competitiveness.

Other sources of revenue could have signaled how driven the institution is by making a profit that I did not include in this study (e.g., private gifts and auxiliary sales). While these

variables are meaningful indicators of private sources of revenue, they did not necessarily indicate market expansion the way distance education, certificates, and private grants and contracts do. For instance, auxiliary sales and services—which include revenue from dormitories, cafeterias, and student stores—demonstrate increased revenue from the student market, but they do not provide information on expanding into student consumer markets of education.

While my selection of variables was guided by Slaughter and Rhoades' (2004) argument that economic competition is causing institutions to change their behavior, it should be noted that the IPEDS data were still limited. There were limitations that affected the extent to which I could truly measure their market involvement. There were no perfect matches, rather only approximations for the different elements of Slaughter and Rhoades' theory. Thus, these variables are to be understood as indicators of how universities are changing their behaviors to become more economically competitive, but they are not exact matches to Slaughter and Rhoades' theory. The reason for selecting these main variables was to use them as indicators of expansion into new markets and industry. Presumably, the more inclined an institution is to expanding into the existing market, the more likely the institution will be to adopt MOOCs.

Internal determinants of institutional change. The above sections describe the main dependent variables and variables of interest, which are the two different indicators of competition. As discussed in the previous chapter, to show quantitatively why an institution adopts an innovation, the ideal model includes both *mechanisms of diffusion* in addition to *internal determinants*. According to the theory underlying the internal determinants model of innovation, much of the reason individuals innovate can be traced back to individual-level, internal reasons (Berry & Berry, 2014, p. 322). For instance, high levels of education provide individuals with the knowledge to find and implement new ideas, while wealth allows them to

take on expensive ideas and absorb the risks of financing such an innovation (Berry & Berry, 2014). Similar hypotheses have been developed about why organizations innovate (Cyert & March, 1963; Rogers, 1983). For instance, organizations of greater size and with greater levels of “slack” resources are assumed to be more innovative than smaller organizations with smaller resources (Berry & Berry, 2014; Cyert & March, 1963; Rogers, 1983). I, in turn, extended these hypotheses to higher education adoption of a disruptive innovation to highlight what factors may enable or prevent an institution or set of institutions to innovate.

Using organizational literature and higher education research to guide my decisions, Table 4 lists the variables that I identified as being internal determinants that may either promote or restrict organizational innovation. I included public status since some studies suggested these institutions are less likely to innovate because they receive state subsidies and are not so dependent on market forces (Brewer et al., 2001; Levine, 1980). On the other hand, some institutions argue that public institutions have been more affected by unrelenting declines in state appropriations, making them more vulnerable to market forces and therefore more likely to change (Altbach et al., 2011; Ehrenberg, 2006; Slaughter & Rhoades, 2004). Given the different expectations for the relationship between public institutions and the adoption of innovation, how this variable is likely to influence disruptive innovation is not yet clear.

To address the ways wealth enables or hinders innovation, I used cash flow, which is the difference between total revenue and total expenditures as well as size of endowment. Institutions that have extra financial slack have the ability to spend more on innovation as well as absorb the risks (Rogers, 1983). Yet, in higher education, there is some discussion that the lack of resources may also lead organizations to innovate in order to become more efficient and cut costs (Ehrenberg, 2006; Levine, 1980; Slaughter & Leslie, 1997). According to Everett Rogers

(1983), organizational wealth may condition institutional change for either resource-rich or resource-poor institutions. Generally, less wealthy organizations will adopt an innovation last, simply because they do not have the available resources to fund innovation or tolerate loss (Rogers, 1983). With regards to MOOCs, an article in *The Economist* (2014) cited an average MOOC cost \$70,000 to produce without citing a source, but Hollands and Tirthali (2014) reported a range of \$200,000 and \$325,000 based on their research. While \$70,000 may be a manageable amount for one course, the higher amount that Hollands and Tirthali listed would certainly tax institutional financial reserves. Ultimately, the wealthier an institution, the more funds it has to draw from to produce an innovation.

Tuition dependence and size of enrollment in combination are very informative variables of institutional vulnerability and therefore probable predictors of innovation. Increasingly, lower-tier institutions, especially private nonprofit ones, have had to increase their institutional grants in order to compete with more prestigious public institutions to attract enrollment (Ehrenberg, 2012). Thus, by using tuition as a percent of total revenue—after adjusting for institutional grants and aid (i.e., the discount rate), I was able to assess how dependent the institution was on that single, yet volatile, financial indicator. Enrollment is an indicator of institutional size. Depending on the model, I either standardized this value ($SD = 1$ and $Mean = 0$) or I used it as a raw indicator. While organizational size is a well-known indicator of innovativeness, I was interested in juxtaposing tuition next to enrollment to assess the average level of vulnerability or strength to innovate. For instance, when a model results show that an institution is highly dependent on tuition and has a relatively small enrollment and the institution innovates, this suggests that the institution may be innovating in order to generate revenue. The opposite may also be true.

Table 4. Indicators of Institutional Capacity

Variable Name	Description	Indicator of Innovation
Public 4Yr (%)*	Public status (1 = public, 0 = private)	Some research suggests government regulation and subsidies depress institutional innovation because institutions are less competitive (Brewer, 2001; Levine, 1980). However, other research on MOOCs specifically suggests a higher correlation with public institutions (Allen & Seaman, 2013).
Cash flow	Total core institutional revenue minus the total expenditure. Represents financial slack.	Cash flow is an indicator of institutional financial vulnerability; the smaller the cash flow, the more financially vulnerable the institution is.
End of year endowment	Funds whose principal is nonexpendable (true endowment) and that are intended to be invested to provide earnings for institutional use. Also includes term endowments and funds functioning as endowment.	Institutions with greater financial slack are more likely to innovate (Berry & Berry, 2014; Cyert & March, 1963). Also found to be true of higher education institutions (DeRousie, 2014; Levine, 1980).
Tuition as % of total revenue	Total net tuition revenue out of total revenue. Where net tuition is the amount of tuition revenue after deducting institutional grants and aid.	The more dependent an institution is on tuition for revenue, the more vulnerable it is. The research suggests that while the lack of financial diversity might deter institutions from innovating, it also may encourage institutions to innovate because of their vulnerability to one source of resources.
Total student enrollment	Indicator of institutional size.	Larger institutions are more inclined to innovate; they are less vulnerable and can control external factors more easily (Berry & Berry, 2014; Cyert & March, 1963; Rogers, 1983).

Empirical Approach

This dissertation employed three different methodologies for each of the questions. The first question employed a discrete time hazard model (DTHM) to identify when and why colleges adopted MOOCs. The second model used descriptive statistics only to describe the relationship between prestige and economic competition and the type of provider an institution partnered with (e.g., for-profit versus nonprofit) and how these relationships changed over time. The third model employed a latent class analysis (LCA) to examine the extent to which a typology of innovating universities and colleges existed. The data combined inform us of the motivations and possible obstacles to disruptive innovation in higher education.

Section 1: Discrete Time Hazard Modeling of MOOC Adoption

Research on the systematic diffusion of disruptive innovation in higher education is nascent. The first strategy I employed to establish what incentivizes higher education institutions to adopt MOOCs was a method common in the social sciences to identify when the rate of adoption is highest and what factors contribute to it. The research questions I addressed in this section specifically were:

1. When is MOOC adoption most likely?
2. How does prestige-seeking behavior compared to economic competition influence the adoption of MOOCs?

Identifying when the rate is most likely and why means analyzing time series data to see what variables affect adoption over time. Event history analysis (EHA), specifically a discrete time hazard modeling (DTHM), is state of the art for doing this type of analysis (Berry & Berry, 2014; Bowers, 2010; Singer & Willett, 2003). Broadly, EHA is ideally suited for examining change over time—specifically, whether and when a particular event occurs. EHA also describes

how the variables of interest affect the amount of time it takes for an innovation to be adopted initially (Singer & Willett, 2003). I selected the DTHM model because the timing of the events is measured in large windows of time (e.g., years, not days). Other models for continuous time hazard modeling also exist, but because adoption happened in such large discrete windows, using continuous models would have been inappropriate (Box-Steffensmeier & Jones, 2004; Doyle et al., 2010; Singer & Willett, 2003). The smaller the unit of analysis for time, the more credible the continuous model would be and vice versa (Allison, 1982). DTHM analyzes the occurrence of *events*, which are records of when a change occurred to a sample (Allison, 2002; Singer & Willett, 2003). For instance, if a sample consists of women of childbearing age, each woman's event history might consist of the birthdates of her children (Allison, 1982, p. 62). In this project, I examined MOOC adoption in academic year increments.

There are several advantages to using DTHM over the commonly used ordinary least squares (OLS) approach. For instance, DTHM incorporates both time-variant and time-invariant explanatory variables and allows estimation of the impact of categorical predictors by using log-linear approaches that are not well-estimated using traditional OLS strategies (Allison, 1982; Singer & Willett, 2003). Another advantage of this model is that it allows for the appropriate handling of missing data through "censoring." If an event is never observed during the time window selected, this is referred to as "right censoring." If the event time is not observed because the occurrence of an event is not known before the start of the study design, this is referred to as "left censoring" (see Singer & Willett, 2003, pp. 316-318). Left censoring typically occurs because of poor study design, in which the researchers did not pay sufficient attention during the design phase to identifying the beginning of time; on rare occasions, left censoring may happen particularly when a researcher is examining repeating events where there is

inevitably a left-censored event from the previous time period (Singer & Willett, 2003). From the perspective of understanding change, the longer the window, the more reason a researcher has for right censoring. According to Singer and Willett (2003), “The validity of survival analysis rests on the assumption that censoring is non-informative, either because it occurs at random or because it occurs at a time dictated by design” (p. 319). Thus, if data are right-censored, they are considered non-informative for the window of time under question. For the present study, the beginning of time was 2011 and the study stopped at the end of the 2014-15 academic year or July of 2015. There were no left-censored data because the study design started with the first course launch in August 2011 when Stanford’s Sebastian Thrun launched the first course called “Introduction to Artificial Intelligence.” Any events not yet experienced were therefore right-censored after the AY 2014-15 academic year. The code for this analysis can be found in Appendix A.

Data structure. Data for DTHM are structured as unbalanced time-series panel data. They are organized in long form, and multiple records describe a specific time period for each individual (Singer & Willet, 2003, p. 352). This is often referred to as the “person-period” dataset, although it is an “institution-period” dataset in the current study. Records increase for each year until an institution adopts a **MOOC**. **At this point, data stop** being recorded for the unit. In the current study, the institution-level dataset was converted into an institution-period dataset, with “event” defined as the first institutional adoption of MOOCs from academic year 2011-12 until the time I stopped data collection (AY 2014-15).

Components of a DTHM. DTHM uses specific terms to describe the different components of the approach. First, the model outcome is referred to as the *hazard rate*. This is the probability of an event occurring in a specific time period, conditional on the fact that the

event never occurred before (Allison, 1982; Singer & Willett, 2003). In practice, it results in the rate of adoption for an institution in a given year. In mathematical terms, the hazard rate is the conditional probability that individual i will experience the event in time period j , given that he or she did not experience it in any earlier time period (Singer & Willett, 2003, p. 330). The hazard rate represents the probability of event occurrence among only the individuals “eligible” to experience the event. This means that if the individual already experienced the event, then this individual is no longer eligible. Individuals who are eligible to experience the event comprise the *risk set*. In the present study, the risk set comprised institutions that had never adopted MOOCs before and were therefore “at risk” of adoption.

A DTHM has several components: the life table, the survival function, the hazard functions, as well as the final analytic table that presents the hazard rates as MLEs. The life table is used to track the event histories of a sample of individuals. In my case, that means tracking colleges and universities, from “the beginning of time” or AY 2011-12 to AY 2014-15 (when no institution adopted a MOOC) through the end of data collection (Singer & Willett, 2003). The importance of the life table is that it depicts the effects of time on the probability of adoption. The hazard function is the function that represents the conditional probability that an event occurs (i.e., the event is conditional on the fact that it never occurred before). It is the *unique* risk of the event happening in *that* time period (Singer & Willett, 2003, p. 331). In the results section, I present the hazard function (functional form) that depicts the unique risk of adopting a MOOC for each year. In comparison, the survival function represents the cumulative period-by-period risk of event occurrence (or non-occurrence) that assesses the probability that an individual will “survive” the event (see Singer & Willett, 2003, p. 334). In the results, I present the functional form for institutional “survival,” which means the college or university does not adopt a MOOC.

Estimating equation for a DTHM. The DTHM uses maximum likelihood estimation to parameterize the equation, allowing the logit hazard to be expressed as a linear function of the time indicators and substantive predictors. The logit hazard is the log odds of event occurrence in that particular time period for the individuals in the given risk set. Log odds are a way of expressing probabilities for binary outcomes, where they are the linear transformations of the odds (Singer & Willett, 2003). However, researchers often use odds ratios to ease interpretation. For that reason, my results are discussed in odds ratios, which were produced when I took the inverse of the log odd ($e^{\log odd}$). The estimating equation for the DTHM for this study can be written as follows:

Equation 1. Discrete time hazard model equation

$$ADOPT_{i,t} = a_1 2011_1 + a_2 2012_2 + a_3 2013_3 + a_4 2014_4 + \gamma'(Prestige)_{i,t} \\ + \delta'(Market)_{i,t} + \phi'(Covariates)_{i,t}$$

where $ADOPT_{i,t}$ is the conceptual dependent variable, which are the log-odds that an institution i will adopt a MOOC in year t , given that the state has not adopted a MOOC the year prior. A constant $a_1 2011_1 - a_4 2014_4$ denotes each of the four time periods (AY 2011-12, 2012-13, 2013-14, 2014-15), which are each intercept parameters. The remainder of the equation includes the slope parameters to assess the effect of a one-unit difference on that predictor on event occurrence, statistically controlling for the effects of all other predictors in the model. Specifically, the primary variables of interest for each institution (i) in each time period (t) are where γ' represents a vector of variables for prestige (e.g., research and admissions selectivity); δ' represents the vector of variables for market involvement (e.g., tuition as a percent of total revenue, private grants and contracts as a percent of total revenue, business executives/management as a percent of total revenue, adjuncts as a percent of total instructional staff,

number of courses offered as distance education, and number of certificates offered); and $\boldsymbol{\varphi}'$ represents the vector of institutional characteristics that are representative of the internal determinants (e.g., public versus private nonprofit institution, above median cash flow, above median end of year endowment, and enrollment). Results are reported in the table as maximum likelihood estimates (MLEs) but then converted to odds ratios in the discussion of the results to ease interpretation (Singer & Willett, 2003).

Model fit. A DTHM model includes both baseline characteristics (time) and substantive predictors (e.g., indicators of prestige, economic competition, and institutional capacity). This is different from an OLS model that does not take into account the effects of time. The DTHM is then fit to the data by estimating parameters for each time period and for each of the variables using logistic regression (Singer & Willett, 2003). The model conducts consecutive testing of significance of multiple pseudo-intercepts for each time point, which effectively models the effect of time in the analysis of an institution's risk of adopting a MOOC (Bowers, 2010; Singer & Willet, 2003). Then, the additional parameters are added to the model as β estimates (log-odds), and the model fit is assessed.

When comparing models, the researcher needs to use multiple statistics to assess how well the model fits the data. The models generate a maximum likelihood estimate (MLE) that is the output for a logistical regression that generates a log likelihood (LL statistic). In general, if a researcher fits several competing models to the same data, the larger the LL statistic, the better the fit (Singer & Willet, 2003, p. 116). This means that if the model employed yields negative LL statistics, the values that are smaller in absolute terms or closer to 0 provide a better fit. The "deviance statistic" compares log likelihood statistics for two models, where deviance is the difference between two models multiplied by -2 (Equation 2). That is, for a given set of data, the

deviance compares how much worse the current model is to the best possible model. In tables, the deviance is the same as “-2LL” and the smaller the deviance, the better the fit. Researchers use deviance to run hypothesis tests of different models. The equation for the deviance statistic is:

Equation 2. Deviance equation

$$Deviance = -2LL_{current\ model}$$

The problem with the LL and calculations dependent on the LL is that it inevitably always goes up whenever any parameters are added to the model, so additional statistics are helpful to compare model fits. The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) use the deviance to show model fit. In my study, these tests helped me to compare the relative fit of the model of the prestige-seeking compared to the model of economic competition. Both the AIC (Equation 3) and the BIC (Equation 4) are based on the number of model parameters. They both measure how the fit of one nested model compares to the fit of another nested model. The AIC and BIC penalize the log likelihood statistic for the number of parameters present in the model. The BIC has been shown to be a more reliable statistic than the AIC because in addition to the number of parameters, it also takes into account the sample size (Singer & Willett, 2003, p. 402). I report both the AIC and BIC in my results tables (see Section 1 of Results). The equation for the AIC and BIC are as follows:

Equation 3. AIC equation

$$AIC = Deviance + 2(number\ of\ model\ parameters)$$

Equation 4. BIC equation

$$BIC = Deviance + \ln(sample\ size)(number\ of\ events).$$

Following previous literature, I included a conservative measure, the Cox and Snell index,

and a more liberal estimate of variance, the Nagelkerke R^2 (Bowers & Chen, 2015). Each of these statistics can be used to estimate the amount of variance explained in the model, although they should be interpreted with caution. Researchers have still not been able to find the equivalent index as the R^2 in the OLS model, which is clearly defined as the proportion of the variation in the dependent variable that can be explained by the predictors in the model. Therefore, the Cox and Snell index, the more conservative estimate, is usually best used as a supplement to other indicators of model fit.

Section 2: The Motives of MOOC Adopters

In the DTHM, the rate of adoption and the most influential drivers of disruptive innovation are identified, but this model does not address how the drivers vary among the group of adopters. It only reports statistically significant findings in the aggregate. However, research has suggested that over time, drivers of innovation fluctuate, as do the types of institutions that adopt the innovation (Berry & Berry, 2014; Rogers, 1983). Presumably, this trajectory applies to the adoption of a disruptive innovation as well. Research has also suggested that institutions are motivated by different goals when adopting open educational resources or open courseware. Some goals are very closely related to economic competition (e.g., improving economics and not falling behind the competitors), while others are more closely related to building prestige (e.g., conducting research on teaching and learning) (Hollands & Tirthali, 2014; Walsh, 2011). Therefore, to further examine whether the drivers of disruptive innovation change over time and whether economic competition drives some adopters more than others, I employed a descriptive analysis over the 4 years of data for the 122 MOOC adopters, where the outcome variable was whether an institution partnered with a for-profit or a nonprofit provider. In Section 2, I asked these questions:

1. Does partnership with a for-profit versus nonprofit provider differ by prestige-seeking behavior or economic competition?
2. Do these partnerships change over time?

Empirical approach. Methodologically, this set-up was similar to the first question. My goal was to investigate the relationship between drivers of disruptive innovation and adoption of a MOOC while partnering with either a for-profit or nonprofit provider, assuming the institution has never partnered with a provider before. However, the size of my adopters ($n = 122$) with 10 different substantive predictors prohibited inferential statistics. In order to have enough power, regressions should have approximately 1,000 observations to avoid Type I errors, given the number of independent variables that I wanted to explore (Cohen, 1962, 1992). Given this limitation, the analyses in this section were descriptive statistics (e.g., means testing). I investigated first whether the averages for various drivers of change varied by whether an institution partnered with for-profit compared to nonprofit providers, and then I examined this over time. I employed t-tests and chi-square to explore the statistical significance of the relationships. These tests are used when samples are small and when the distribution is not known to identify whether a statistical difference between the groups exists (Shavelson, 1996). In my study, for instance, in the first year, there were only nine adoptions (e.g., three partnerships with nonprofit providers and six partnerships with for-profit providers). The outcome variable was a binary indicator variable for adoption with a for-profit or nonprofit provider (0 = nonprofit; 1 = for-profit provider). Independent variables included the measures of prestige and the measures of economic competition. The code for this section can be found in Appendix B.

Data structure. This analysis used the same panel data employed in the first analysis.

What differed in this study was the outcome variable: for-profit versus nonprofit (1= for-profit; 0 = nonprofit). There were 122 instances of adoption with a for-profit or nonprofit provider from AY 2011-12 to 2012-14. For-profit and nonprofit providers were created by collapsing the providers into a dichotomous variable. Table 5 shows the emergence of the different MOOC providers over the years of data collection. The majority of providers were for-profit. In the end, 95 of the institutions partnered with a for-profit provider, while 27 partnered with a nonprofit provider.

Table 5. Emergence of Providers Over Time by Number of Partnerships

Provider	For-Profit	2011	2012	2013	2014	Total
Coursera	x	5	20	10	2	37
Canvas	x			12	22	34
Open Education by Blackboard	x		2	18	1	21
edX		1	1	6	8	16
Independent		1	3	2	2	8
Janux	x		1			1
Kadenze	x				1	1
MOOC-ED				1		1
MRUniversity		1				1
Udacity	x	1				1
Udemy	x		1			1
Total		9	28	49	36	122

Section 3: Latent Class Analysis (LCA)

The purpose of this dissertation was to investigate the systematic drivers of disruptive innovation and the ways these drivers varied over time in order to better understand what obstructs and facilitates disruptive innovation. The first analysis of when and why institutions adopted MOOCs shed light on how time and various institutional characteristics affected the rate of adoption of an innovation. However, this model was limited in its ability to show how the drivers varied over time and according to different institutional preferences; in other words, it

treated all MOOC adopters as the same. The second model analyzed the adoption patterns of institutions more closely, by only examining the adopters to identify the ways in which partnership with a provider differed by different drivers and whether these relationships varied over time. While useful for highlighting differences in institutional behaviors over time, this model was limited to a very small sample and is not generalizable to all innovators. To reconcile these issues, in the last model I employed a latent class analysis (LCA) to ultimately derive a typology of institutional innovators that is both generalizable and attentive to the observational differences across all colleges and universities in my sample.

To investigate whether there were latent groups of innovators, I used LCA, which has been widely used in the social and behavioral sciences to create risk groups (e.g. Lanza & Rhoades, 2013), but it has only recently debuted in education (Bowers & Sprott, 2012; Denson & Ing, 2014). LCA is part of an emergent field of statistics that uses *mixture modeling* to identify homogeneous subpopulations in a larger heterogeneous population (Jung & Wickrama, 2008; Masyn, 2003; Muthén, 2002, 2004; Samuelson & Raczynski, 2013). Finite mixture modeling refers to modeling with categorical latent variables that represent subpopulations where population membership is not known but inferred from the data (Muthén & Muthén, 2012). LCA posits that there exists a *latent* (unobserved) categorical variable that divides a population into mutually exclusive latent classes (Jung & Wickrama, 2008; Lanza & Rhoades, 2013; Lazarsfeld, Henry, & Anderson, 1968).

LCA is often viewed as a type of clustering analysis. However, in traditional clustering models, the focus is on the structure of the variables, whereas in LCA the focus is on the cases (Samuelson & Raczynski, 2013, p. 306). The goal of LCA is to classify individuals (or institutions) into distinct groups or categories based on individual response patterns. This then

allows the creation of subgroups, where institutions within a group are more similar than institutions between groups (Jung & Wickrama, 2008b). I selected LCA as the analytic technique in this dissertation because it evaluates how groups of institutions differ or relate to one another (Graves & Bowers, in press).

Latent class model. LCA is a type of mixture model that has two parts: a *measurement model* and a *structural model*. The *measurement model* for LCA is a multivariate regression model that describes the relationship between a set of observed dependent variables and a set of categorical latent variables (Muthén & Muthén, 2012, p. 153). The observed dependent variables are referred to as *latent class indicators*, where the relationships are described by a set of logistic regressions equations for binary or ordered categorical latent class indicators. The *structural model* for LCA describes three different relationships in one set of multivariate equations: (a) the relationships among the latent categorical variables; (b) the relationships between the categorical latent variables; and (c) the observed values that are not latent class indicators (p. 154). The relationships in the structural model are described by a set of multinomial logistic regression equations for categorical latent dependent variables.

To compute the number of classes, the model uses an expectation-maximization (EM) algorithm, which is an iterative method that alternates between performing an expectation (E) step that uses the parameter estimates and creates an expectation of the log-likelihood and, in the next step, the model computes the parameters that maximize the expected log-likelihood found in the E step. Then these parameter-estimates are then once again used to determine the distribution of the latent variables in the next iteration of the E step (Dempster, Laird, & Rubin, 1977). The point of this procedure is to iterate enough times to identify a global maximum of getting a particular outcome given a particular class. To avoid finding a local min and local max, different

sets of starting values are produced, where the solution with the best likelihood is reported in the output. Researchers can change the number of start values manually as well using Mplus, in order to ensure that the best likelihood is replicated (Asparouhov & Muthén, 2012).

In practical terms, to identify the number of classes, the LCA performs hypothesis-testing for K number of latent subgroups that must be inferred from a set of latent class indicator variables (Boyce & Bowers, 2016; Lanza et al., 2013). Ultimately, the data fit indices help the researcher to identify the relative adequacy of a $(K-1)$ -class model compared to a K -class model (Dziak, Lanza, & Tan, 2014). The LCA model uses latent class indicators (i.e., the observable indicators) to estimate the parameter values for the model. The model includes two parameters. The first is the prevalence of each of “C case” subpopulations, which are known as *latent classes*. A *latent class* means that the case’s class membership is not directly observed. A second parameter is the *conditional response probabilities*. That is, for each combination of latent class, there exists a probability that one of the members of the latent class will answer “yes” to one of the survey items, the latent class indicator which is a *manifest variable*. Manifest variables are observable in the data. For example, in my study, a manifest variable was whether or not the school was a research institution, public, or whether it was above the median in terms of tuition revenue (see discussion below on why I dichotomized continuous variables). Then, a *conditional response probability* parameter would be the probability that a member of, say, “Latent Class 1” answered “yes” to the question about whether it was public or not. It is conditional because once the member of the class answered “yes,” then the probability that it was not public was also known since one probability was subtracted from the other from 1.0. Each of these parameters was estimated using a maximum likelihood estimation, which requires iterative computation in order to achieve the values that optimize the criterion (Lazarsfeld et al., 1968; Ubersax, n.d.).

Once the number of classes was established based on statistical and substantive interpretation (see discussion on “Model Fit and Determining Number of Classes” below), then a case (e.g., the institution) could be classified to its most likely latent class.

For an example of the structural model, see Figure 1. The arrows run from “C”—the latent class dependent variable—to the latent class indicators that were selected based on my theory (e.g. competition plus internal determinants are expressed in different combinations of latent classes). The direction of these arrows is intentional and indicates that the threshold of the latent class indicators vary across the classes of C, implying that the probabilities of the latent class indicators varied across the classes of C. The arrows show the latent class indicators were regressed on a set of dummy variables that represented the subgroups of C. The AUXILIARY command in Mplus allows the researcher to specify variables that are not part of the analysis that are important predictors of latent classes using a three-step approach (Asparouhov & Muthén, 2014; Muthén & Muthén, 2012).

The mathematical equation, according to Lanza and Rhoades (2013, p. 159) for LCA can be expressed this way (Equation 5). Let Y_j represent element j of response pattern y . The indicator function is $I(y_j = r_j)$, which equals 1 when the response to $j = r_j$. Otherwise, it is 0. The probability of observing a particular vector is:

Equation 5. Generic equation for LCA

$$P(Y = y) = \sum_{c=1}^C \gamma_c \prod_{j=1}^J \prod_{r_j=1}^{R_j} \rho_{j,r_j|c}^{I(y_j=r_j)},$$

where γ_c is the probability of membership in latent class c and $\rho_{j,r_j|c}^{I(y_j=r_j)}$ is the probability of response r_j to item j given member in latent class c . The γ parameters are a vector of latent class membership probabilities that sum to 1. The ρ parameters represent a matrix of item-response probabilities that are conditional on membership to a latent class. In this particular formula, the

degrees of freedom are calculated as the number of possible combinations minus the number of freely estimated parameters (Muthén & Muthén, 2012).

Structural and conceptual model of LCA. Figure 1 presents the spatial and conceptual model of the LCA of Innovation with MOOC adoption as a distal outcome. The subgroups of specific policy contexts in which innovation occurs (“Latent Class C”) are estimated in terms of the three distinct institutional attributes that derive from the theory of this dissertation (Prestige, Market Involvement, and Institutional Capacity). The subgroups are used to predict MOOC adoption.

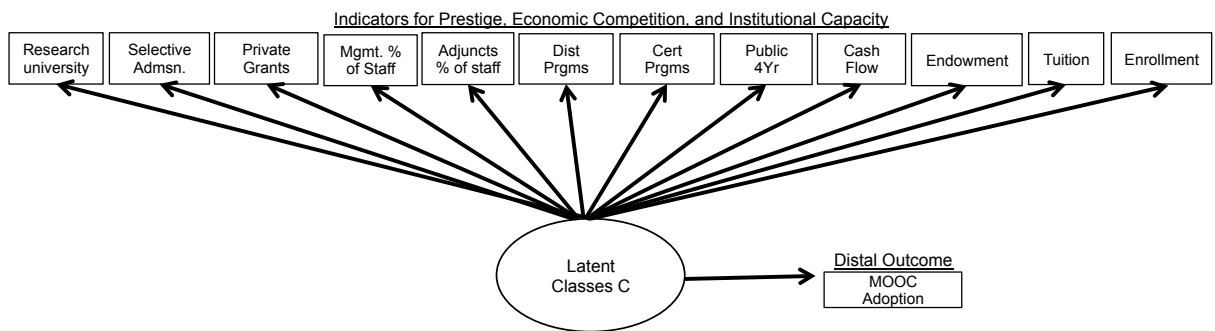


Figure 1. Structural and conceptual equation model for LCA of MOOC adoption

Model fit and determining the number of classes. Like the DTHM, a variety of fit statistics was employed to identify whether the model fit the data well. Researchers (e.g., Lanza & Rhoades, 2013) use the chi-square goodness-of-fit test to examine model fit among other fit statistics. However, those statistics can sometimes be problematic in LCA. Chi-square goodness-of-fit tests are usually used to compare nested models; however, most LCA models do not compare nested models with different number of parameters, but only the number of classes. As such, an chi-square test is not appropriate (Samuelson & Raczynski, 2013).

To compare the models with different classes, researchers have used the AIC and BIC,

like those used in the DTHM. Across all of these criteria, a lower value suggests a more optimal balance for model fit and parsimony. However, because the AIC does not include sample size, the BIC or adjusted BIC is preferred (Nylund, Asparouhov, & Muthén, 2007; Samuelson & Raczynski, 2013). At the point that the BIC starts to rise, the K-1 class is the correctly identified class. Another measure, called the Lo-Mendell-Rubin (LMR) test, uses the approximation to the likelihood ratio distribution. Again, the fact that the class before the LMR was no longer significant signals that the model fit was best.

Other measures of examining model fit include class quality, which is referred to as *entropy*. Entropy measures how clearly or confidently a model classifies the subjects in terms of the posterior probabilities (Dziak et al., 2014). Models in which entropy approaches 1.0 indicate that there is clear delineation between classes (Samuelson & Raczynski, 2013).

According to Samuelson and Raczynski (2013), estimated conditional probabilities approaching the boundaries of 0 or 1 may indicate that the data may have been overfit. In some cases, the researcher may want to simplify or restrict the model in order to prevent issues that call into question the confidence intervals and significance tests.

LCA also includes covariates and distal outcomes that are commonly referred to as auxiliary variables. These are variables that are not used in the initial analysis to identify the classes. Oftentimes, researchers are interested in using latent class membership to predict the likelihood of the given outcome variables. However, given that the class assignment is not known with certainty, predicting outcomes from K-classes is statistically problematic. Standard errors are often biased, resulting in incorrect significance tests. Recent research has found that distal outcomes that are binary or categorical are not subject to the same bias as continuous variables (Lanza & Rhoades, 2013). My outcome was dichotomous and therefore did not

encounter these issues.

Distal outcomes and three-step approach. While the LCA uses observed data to predict a latent outcome, scientists are often interested in understanding the relationship in the opposite direction, in which the predictor is latent and the outcome is manifest. More precisely, the investigation is of the conditional distribution of a Distal Outcomes “Z,” given a latent class Variable C (Lanza et al., 2013). In Figure 3, the “Z” is the distal outcome “MOOC Adoption.” Setting up the prediction model as such allows for this type of model to predict many other types of disruptive innovations, not just MOOCs. Thus, that is the major contribution of using this model. The Z distal outcome does not affect the creation of the classes, but by using the relationship between the latent classes and the adoption of MOOCs, I can show how the different confluence of characteristics and behaviors influences disruptive innovation, enabling a better sense of how systematic disruptive innovation takes place.

To estimate the relationship between the latent class C and the distal outcome (e.g MOOC adoption), I used a variation of the three-step approach with the auxiliary command (DCAT) with the distal outcome MOOC adoption, as recommended by the literature (Asparouhov & Muthén, 2014; Lanza et al., 2013). Traditionally a three-step model includes a second step that measures how the covariates vary among the different subgroups; however, I do not assess the variation of covariates in this model, and so I skip directly to the third-step that assesses the relationship between latent class subgroups and the distal outcome, MOOC adoption. Thus, after the number of classes has been determined and the institutions have been probabilistically assigned to the classes, I employed a three-step procedure, which uses the AUXILIARY command (DCAT) to assess categorical distal outcomes.

Using a model-based approach to analyzing the distal outcome is preferred to doing a

post-hoc analysis (Asparouhov & Muthén, 2014; Lanza & Rhoades, 2013; Lanza et al., 2013). According to the research, simulation studies have shown that the model-based approach, compared to the classify-analyze approach (i.e., post-hoc multinomial logistic regression), produces less biased estimates of the effects (Lanza et al., 2013). This is because when done separately, there is uncertainty related to class-membership; second, and more concerning, is that the standard classify-analyze approach imputes the latent variable under a model that is not sufficiently general, resulting in attenuated standard errors (Lanza et al., 2013, p. 2). The benefits of running a three-step model with a distal outcome are that the latent class is regressed on the predictor variables, while taking into account any misclassification that occurred in the second step; if covariates are included, then a kernel density estimation approach is taken—an approach that uses repetitive pseudoclass draws to find a maximum probability assignment to the distal outcome (Lanza et al., 2013).

Data structure. Finally, the data structure for LCA requires cross-sectional data where the predictors are either dichotomous or polytomous. The model uses maximum likelihood estimates that are based on conditional probabilities of cases *endorsing* (i.e., saying “yes”) to a survey item. When a case (i.e., a university) reports “yes” on the item, the equality constraint assumes that the conditional probability of saying “no” is therefore the probability of 1 minus the probability of saying “yes.” For this reason, variables need to be entered in such a way that the equality constraint is met. Because my variables included continuous variables, I collapsed continuous items into dichotomous variables, according to above the median or at or below the median, where above the median was coded 1 and at or below the median was coded 0.

The following measures were dichotomized:

- High research from the Carnegie Classification (1 = research university; 0 =

Bachelors, Masters, Other);

- High selectivity (1 = above the median of admissions selectivity, 0 = at or below the median);
- High contract (1 = above the media, 0 = at or below the median in terms of private grants and contracts as a percent of total revenue);
- High managers/business executives (1 = above the median, 0 = at or below the median in terms of managers/business executives as a percent of total staff);
- High adjunct (1 = above the median, 0 = at or below the median in terms of adjuncts as a percent of total instructional staff);
- High distance (1 = above the median, 0 = at or below the median in terms of the number of distance education courses and programs offered);
- High certificates (1 = above the median, 0 = at or below the median in terms of certificates offered by all institutions);
- Public (1 = public; 0 = private);
- High cash (1 = above the median, 0 = at or below the median in terms of cash flow, which is calculated by taking the difference between total revenues and total expenditures);
- High endowment (1 = above the median, 0 = at or below the median in terms of end or year endowment);
- High tuition (1 = above the median, 0 = at or below the median in terms of net tuition as a percentage of total revenues);
- High enrollment (1 = above the median, 0 = at or below the median in terms of total student enrollment).

Because of these advanced calculations and the power required to iterate many data over again, LCA requires separate software than traditional statistical packages. While data were prepared in Stata 14.0, all statistical procedures were performed in MPlus, version 7.4 (Muthén & Muthén, 2012). The MPlus code used for this analysis is included in Appendix C.

Chapter 4: Results

The process of disruptive innovation in higher education is not well understood despite the growing interest in using developments in technology to transform it. The purpose of this study was to use competing theories of institutional change to investigate how systematic disruptive innovation takes place. In this study, I used the rapid expansion of MOOCs to investigate how institutional prestige and economic competition, over a 4-year time span, drove disruptive innovation in higher education.

The research questions were:

1. When is MOOC adoption most likely? How does prestige-seeking behavior compared to economic competition influence the adoption of MOOCs?
2. Does partnership with a for-profit versus nonprofit provider differ by prestige-seeking behavior or economic competition? Do these partnerships change over time?
3. To what extent does a typology of institutional innovators based on prestige-seeking behavior and economic competition exist? To what extent does this typology of innovators relate to MOOC adoption? How does the adoption of innovation by institutional subgroup vary over time?

As discussed in the conceptual framework, this research approached understanding the process of systematic disruptive innovation by using the policy diffusion framework known as the internal determinants and diffusion model. Policy diffusion scholars use this model to explain why a state or jurisdiction adopts a new program or policy. Similarly, I employed this model to test why higher education adopted MOOCs, a disruptive innovation. I borrowed from the diffusion scholars because this model has been well-tested and has endured over the years (Berry & Berry, 1990; 2010; Berry & Baybeck, 2005; Cohen-Vogel et al., 2008; Doyle et al., 2010;

Shipan & Volden, 2006; Walker, 1969).

Using this framework, I considered two different mechanisms of competition: economic competition and competition for prestige. According to the prestige hypothesis, institutions seek change to generate prestige, whereas in the economic competition framework, institutions seek change to generate revenue. Slaughter and Rhoades (2004) postulated the *theory of academic capitalism* to suggest that institutions are shifting from a public good learning/knowledge regime to an academic capitalist learning/knowledge regime, which creates conditions in which the boundaries between the state, the market, and higher education are blurred. Institutions use public dollars provided by federal student loans and state aid to embark on activities that change institutional priorities from unfettered expansion of knowledge to prioritizing revenue generation (p. 36). Thus, because institutions prioritize revenue generation, *economic competition* becomes their primary motivation to change. When applying this framework to MOOCs, one might suggest that the rapid adoption of MOOCs is an outcome of the proposed shift towards an academic capitalist regime. Moreover, as time passes, new entrants offer MOOCs and evidence of competition increases.

An alternative explanation to the market theory of institutional change is higher education's pursuit of prestige (Brewer et al., 2001; Christensen & Eyring, 2011; Marginson, 2006). Some researchers have argued that colleges and universities are not responsive to economic competition, but instead are more responsive to acquiring prestige, which helps to secure a constant supply of resources, donor support, and research dollars (Brewer et al., 2001). Because prestige is a zero-sum game, institutions seek it to amass more of the limited resources reserved for prestigious institutions.

While multiple points of difference in the mechanisms are emphasized by these two

perspectives, the most relevant difference in their empirical predictions concerns which types of institutions are most likely to be disruptive innovators and under which incentive structure.

While the pursuit of both economic and prestige gains might come into play, the relevant influence of each on a given type of institution might be important as far as designing policy that effectively induces systematic transformative change in higher education.

This dissertation modeled the diffusion of MOOCs from AY 2011-12 to AY 2014-15 to assess the extent to which prestige and economic competition drove the systematic adoption of MOOCs. The indicators for prestige are two variables: a collapsed Carnegie Classification (e.g., research institution, Bachelors, Masters, and Religious/other institutions) and selectivity (a measure of what percentage of applicants the institution rejects). To measure economic competition, I used five variables: percent of revenue from private contracts and grants, management as percent of staff, adjuncts as percent of instructional staff, number of distance education programs, and number of certificate programs. In order to account for other capacity issues that have been shown to influence organizational innovation, I also included a set of institutional capacity indicators. For more information regarding the construction of these variables, see Chapter 3.

Results for each question are presented in sequential order below. The first section employs a discrete time hazard model (DTHM) to estimate the relationship between competing drivers of innovation and the adoption of MOOCs. The second section employs descriptive analysis to evaluate the change in the relationship between drivers and adoption of MOOCs over time. The third section employs a latent class analysis (LCA) to investigate the extent to which there exists a typology of innovators that can then be used to explain the adoption of MOOCs and, potentially, other disruptive innovations in the future. These three approaches help to shed

light ultimately on the drivers of disruptive innovation. More specifically, the ultimate results show whether economic competition, the preferred antidote to inducing institutional innovation, compared to prestige-seeking, is an effective strategy for inducing institutional change.

Section 1. The Determinants of MOOC Adoption

With costs of higher education continuing to rise, identifying what factors lead to more rapid transformation of higher education is becoming a key topic of concern for policymakers, researchers, and education technology specialists. Although policy and politics use economic competition to induce disruptive innovation, there is little research on whether this is an effective strategy (Brewer & Tierney, 2010). The literature has proposed several competing notions of what drives change. On one hand, there is wide agreement that the neoliberal political-economy compels organizations, including higher education, to be more competitive and efficient (Bowen, 2015; Brewer & Tierney, 2010; Christensen & Eyring, 2011; Slaughter & Rhoades, 2004). However, another body of literature has argued that seeking and acquiring prestige drives innovative behavior (Brewer & Tierney, 2010; DeRousie, 2014). Hence, what drives innovation is unclear. Thus, this section asks the following research questions:

1a. When is MOOC adoption most likely?

1b. How do the competing incentives influence the adoption of MOOCs?

Empirical Approach

The empirical approach employs a discrete time hazard model (DTHM). In a DTHM, there is a *risk set*, which is the group of colleges and universities that are at any point *eligible* to adopt a MOOC. The dependent variable is the maximum likelihood estimate that a college or university adopted a MOOC, assuming it never has before. Once a college or university has adopted a MOOC, it is no longer eligible to be included in the risk set. The advantage of using a

DTHM, as was discussed in greater detail in the methods section, is its ability to handle time invariant and time variant measures. For instance, in studies that span many years, time variant data such as financial resources are controlled for and do not skew the probability of adoption. The use of DTHM also assumes the adoption of a new policy or program is not going to remain constant over time (Berry & Berry, 2014, p. 331). Institutions may learn from each other, and this may drive up or down the probability of adoption over time. The DTHM allows for right censoring of data. Right censoring takes place when an individual has not experienced the event by the end of the study window and so the “event” time is unknown. For instance, in the case of my study, many institutions continued to adopt MOOCs after the years included in my study design. This meant many institutions were censored, but it did not affect my ability to determine whether prestige or economic competition was more strongly associated with the adoption of MOOCs. The results of a DTHM are presented as maximum likelihood estimates (MLEs), but the findings will be reported in odds-ratios to ease interpretation.

There are several components of a DTHM: the life table, the survival function, the hazard functions, as well as the final analytic table that presents the hazard rates as MLEs. The life table tracks the event histories of a sample of individuals, or in my case, colleges and universities, from “the beginning of time” (when no institution has adopted a MOOC) through the end of data collection (Singer & Willett, 2003). This depicts the effects of time on the probability of adoption. The hazard function is the function that represents the conditional probability that an event occurs (i.e., the event is conditional on the fact that it never occurred before). It is the *unique* risk of the event happening in *that* time period (Singer & Willett, 2003, p. 331). Figure 2 presents the hazard function. This graph depicts the unique risk of adopting a MOOC for each year. The survival function represents the cumulative period-by-period risk of event occurrence (or non-

occurrence) that assesses the probability that an individual will “survive” the event (see Singer & Willett, 2003, p. 334). Figure 3 reports the trends for institutional “survival,” which means the college or university does not adopt a MOOC.

The analytic sample includes 122 4-year colleges and universities that adopted MOOCs out of 1,470 institutions total in my study. This translates into approximately 8% of the sample adopted MOOCs over the 4-year time span. The years included are AY 2011-12 through AY 2014-15. In brief, the final results show that the rate of adopting MOOCs was highest in 2013, and that both prestige and economic competition are positive predictors of MOOC adoption. However, there was stronger evidence of prestige than of economic competition.

Finally, the models presented in this section are loosely modeled on an empirical model used by Doyle, McLendon, and Hearn (2010), who tested competing theories of the adoption of prepaid tuition versus savings plans in the American states from 1986 to 1999. Although they used a different kind of event history analysis that treats time as a continuous variable rather than as discrete, and a Cox Proportional Hazard Model that allows comparisons between competing outcomes, their model employed competing hypotheses to identify the drivers of innovation while controlling for time. This suggests that competing theoretical motivations for institutional change could be successfully included simultaneously in an event history analysis. The model proposed here included mechanisms associated with prestige and measures of economic competition that articulated the economic competition framework developed by Slaughter and Rhoades (2004). I included prestige measures and economic competition measures as separate models to show how they first compared to the baseline and the final model, and then included the fully saturated model.

Descriptive Results

Table 6 presents the means for the sample (n = 1,470) for all 4 years of data collection (AY 2011-12 to AY 2014-15). The means are the averages for all predictors for the full sample of colleges and universities.

Table 6. Descriptive Variables and Frequencies

N=1,470	Population Mean (1,470)
<i>Prestige</i>	
Research	17.96
Masters	37.89
Bachelors	33.72
Religious/Other	10.43
Admissions Selectivity	35.82
<i>Economic Competition</i>	
Private grants and contracts (% of rev)	1.22
Management (% of total staff)	10.65
Adjuncts (% of total teaching staff)	15.96
Total Distance Programs	2.91
Total Certification Programs	3.33
<i>Institutional Indicators</i>	
Public 4Yr	33.74
Cash flow (millions)	27.80
End of Year Endowment (millions)	275
Enrollment	6910
Tuition (% of total rev)	55.72

Most colleges were either Masters (38%) or Bachelors (34%) degree-awarding institutions. On average, institutions rejected approximately 35% of their applicants. With regard to measures of economic competition, a very small percentage of their revenue came from private contracts and grants (1.22%). Mid-level and senior-level managers (listed as managers) comprised almost 11% of total FTE staff, while about 16% of FTE teaching staff were adjunct professors. On average, each institution offered approximately three certification and distance education programs. Approximately 34% of the institutions were public. Cash flow, a measure used to represent the

financial slack of an institution, was roughly 28 million dollars, while endowments averaged 275 million dollars. The average enrollment size for undergraduate and graduate students was almost 7,000 students. Finally, most schools relied on net tuition to make up about 55% of their total revenues. Net tuition is the amount of revenue a college or university receives after adjusting for institutional grant aid awarded to the students.

MOOC adoption. Table 7 presents the results of the life table, which reports the cumulative adoption of MOOCs over the 4 years of data collection. The life table reports the number of adopters by year, as well as what proportion of the sample the adopters constitute year by year, the rate of adoption by year, the rate at which adoption is most likely (the hazard rate), and what proportion of non-adopters persist (survival rate). According to the results, the hazard rate was the highest during AY 2013-14, the third year after their first launch. That means that the rate of adoption, given that no institution in that group had ever adopted a MOOC before was the highest compared to any other year of adoption in the data collection window.

Slightly more than 3% of the college and university population adopted MOOCs during AY 2013-14. Of the 1,470 institutions to start, 122 adopted MOOCs and 1,348 were right-censored (i.e., no event was observed for those schools). That is, 92% of the remaining colleges and universities still had not adopted a MOOC by the end of data collection. The survival rate in the last year was 97%. This indicates that the “at risk” of adopting MOOCs was very low.

Table 7. Life Table for the Event Histories for the Adoption of MOOCs (n = 1,470)

Year	Number of Institutions	Censored	MOOC Adopters	Proportion of MOOC Adopters (Hazard Rate)	Proportion of Non-Adopters (Survival Rate)	Cumulative Proportion Surviving at End of Interval
2010	1470	0	0	0.000	1.000	1.000
2011	1470	0	9	0.006	0.994	0.994
2012	1461	0	28	0.019	0.981	0.975
2013	1433	0	49	0.034	0.966	0.941
2014	1384	1348	36	0.026	0.974	0.917

Figures 2 and 3 graphically depict the estimated hazard probability and estimated survival probability of MOOC adoption over the 4 years of data. Hazard and survival estimates can uniquely demonstrate how the rate of adoption changes, based on the number of institutions still eligible for MOOC adoption. Figure 2 can be read as the percentage at risk of experiencing the event at each specific time point in the dataset such that the proportion changes over time as more colleges and universities adopt MOOCs. For instance, AY 2011-12 had a less than 1% chance of MOOC adoption, followed by a risk of about 2% in AY 2012-13, almost 3.5% in AY 2013-14, and only 2.6% AY 2014-15. Figure 3 shows that the drop-off of further MOOC adoption was fairly substantial in AY 2014-15.

Figure 3 depicts the survival function, which is very high. Formally, the survival function is defined as the probability that the individual or institution, i , will survive past time period j (Singer & Willett, 2003). According to Singer and Willett (2003), over time, as an event occurs, the survivor function declines towards 0. At times when the hazard is high, the survivor function drops quickly. When the hazard is low, however, the survivor function will drop more slowly. The survivor function will never increase (i.e., it monotonically decreases). When passing through a

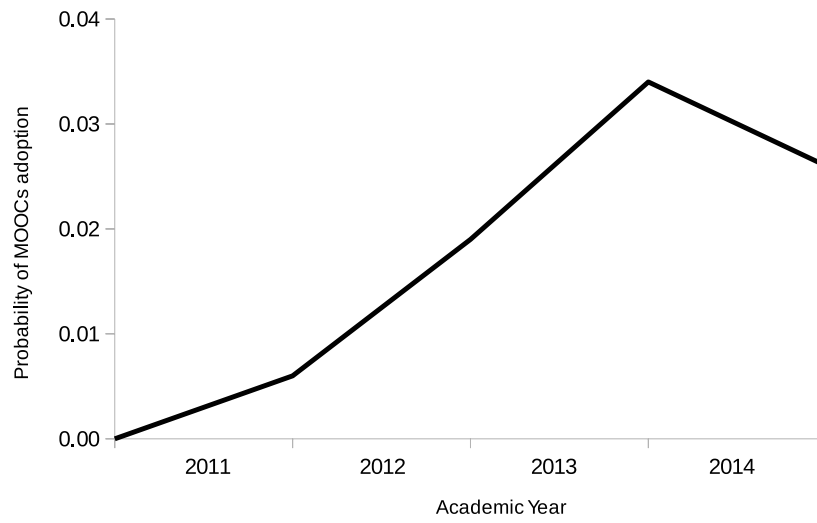


Figure 2. Estimated hazard probability

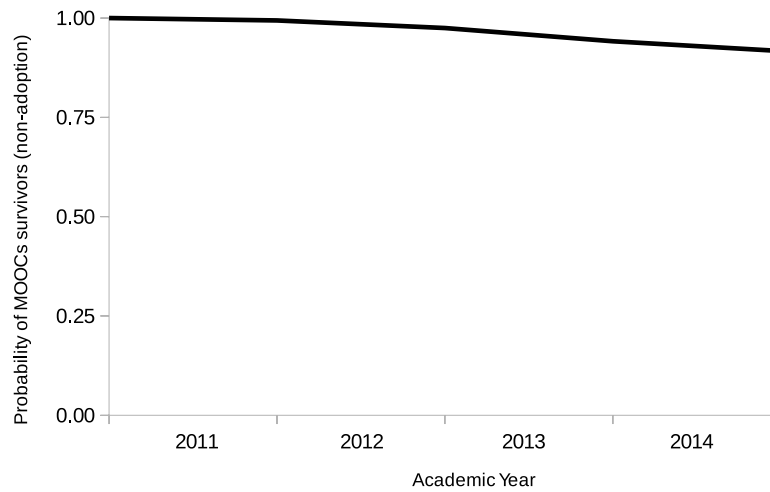


Figure 3. Estimated survival probability

period in which no event occurs, the survivor hazard will simply remain at its previous level. Over time, as the hazard of adopting a MOOC decreases, the survival rate begins to decline at a slower pace. The probability of adoption changed over time, but still for all 4 years of data, adopting MOOCs was not very likely despite all the hype that surrounded their adoption.

DTHM results. The main results for the DTHM are presented in Table 8, which reports how drivers that are time invariant (e.g., public) or time variant (e.g., selectivity) affect the likelihood of adopting a MOOC. The results suggested that when controlling for all else, both indicators of prestige (e.g., Carnegie Classification and selectivity) and some indicators of economic competition (e.g., the percent of revenue coming in from private grants and contracts and the number of distance education programs) were positively associated with the likelihood of adopting MOOCs. Size of endowments and number of students enrolled also positively influenced adoption of MOOCs.

A DTHM was fit to the data by estimating parameters for each time period and for each of the competing hypotheses: measures of prestige and for economic competition (Table 8). The final model included institutional variables that were also linked to institutional innovation in the literature: public status, tuition as a percentage of total income, cash flow, and enrollment. Results included parameter estimates and significance levels, standard errors (in parentheses), and tests of model goodness-of-fit, including -2 Log likelihood, chi-square, Cox & Snell pseudo R^2 , and the Nagelkerke R^2 . Since MOOCs were not enacted until the 2011-12 academic year, there are no intercept parameters for years prior to 2011. With 2011 as the starting point, the model then begins by conducting a test of significance of multiple pseudo-intercepts for each time point in the study in order to estimate the effect of time in the analysis of an institution's risk of adopting a MOOC (Bowers, 2010; Singer & Willet, 2003). The results of a DTHM are

presented as maximum likelihood estimates (MLEs), but the findings will be reported in odds-ratios to ease interpretation.

The DTHM includes five separate models that separate the effects of the competing indicators associated with institutional change. Time is denoted by AY 2011-12 through AY 2014-15. The first step to interpreting results is to identify which model has the best absolute fit. There are several ways of doing this. When examining model fit, researchers often use the log likelihood as a base for joint significance testing. A joint significance test explores whether the inclusion of multiple dichotomous and continuous predictors entered as nested models improves the model fit compared to the saturated model (Singer & Willett, 2003, p. 398). On its own, the log likelihood will always increase when more parameters are included in the model, so it is not necessarily a good measure of fit. The -2 log likelihood (-2LL), which is also called the deviance statistics, measures how much worse the model is in comparison to the best possible model that could be fit. That is, the better the fit of the model, the smaller the deviance will be. In this case, Model D has the most parameters (18) and the smallest deviance (776.73). When the difference in deviance is small compared to the critical chi-square value, researchers fail to reject the null hypothesis, which indicates that the reduced model is not substantively worse than the less parsimonious model (i.e., the model with more parameters).

Researchers also use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to measure how the fit of one nested model compares to the fit of another nested model and then compare these to the fully specified model. The AIC and BIC essentially penalize the log likelihood statistic for the number of parameters present in the model. The BIC is slightly more rigorous in that it also bases model fit on the sample size. In the model presented in this paper, Model D has the smallest AIC and BIC values, suggesting that, again,

Model D has the best fit of any of the other models, even though it has the greater number of parameters ($AIC = 776.73$; $BIC = 850.73$).

Finally, though variance estimates in models that produce MLEs are not equal to the variance of the traditional R^2 of OLS, the Cox & Snell Pseudo R^2 and the Nagelkerke R^2 play an analogous role in MLE models (Bowers, 2010). The pseudo R^2 also helps to indicate model fit, and helps a researcher choose between models. For example, the Cox & Snell model is a ratio of the full model over the intercept model, where the smaller the ratio, the greater the improvement of the model (IDRE UCLA, 2017). The Cox & Snell has an upper boundary that is less than 1. Therefore, some researchers have reported the Nagelkerke pseudo R^2 , which is an adjusted Cox & Snell pseudo R^2 that forces the range of the pseudo R^2 to be between 0 and 1.

The Cox & Snell Pseudo R^2 shows that Model D explains slightly more variance (71.1%) in the probability of an institution adopting MOOCs compared to the other models. A much less conservative estimate, the Nagelkerke R^2 suggests that the model explains 95% of the variance. The amount of variance explained here is high, which is unusual. On one hand, this high level of variance can be explained by the very few number of MOOC adopters. On the other hand, it is well known that logistic regression pseudo R^2 calculations are notoriously inaccurate as they approach 1.0 since there is no true R^2 for logistic regression analysis of this (Bowers, 2010; IDRE UCLA, 2017). Bowers (2010) noted that once the amount of variance explained by the equation exceeds 0.5, the interpretation of the accuracy of that model must be considered with caution. However, the variance in this model does seem to explain considerably more than what DeRousie's (2014) model was able to explain. For instance, Model D as well as the other models in my analysis explained more of the variance of adopting a MOOC (Cox & Snell = 0.71) compared to DeRousie's study on the adoption of MOOCs (Pseudo $R^2 = 0.561$), which suggests

Table 8. Results of Fitting Five Discrete Time Hazard Models to Year of First Adoption

	Model A	Model B	Model C	Model D
AY 2011-12	-5.01*** (0.33)	-8.00*** (0.52)	-4.45*** (0.40)	-6.99*** (0.80)
AY 2012-13	-3.87*** (0.19)	-6.83*** (0.42)	-3.25*** (0.29)	-5.44*** (0.73)
AY 2013-14	-3.31*** (0.15)	-6.13*** (0.39)	-3.17*** (0.271)	-4.86*** (0.68)
AY 2014-15	-3.62*** (0.17)	-6.40*** (0.40)	-3.54*** (0.29)	-5.17*** (0.68)
Prestige				
Research university ^b		2.95*** (0.30)		1.26*** (0.39)
Masters university ^b		0.46 (0.37)		0.11 (0.4)
Religious/Other ^b		0.24 (0.53)		0.48 (0.55)
Admissions selectivity		0.04*** (0.00)		0.03*** (0.01)
Economic Competition				
Private contracts/grants as % of total rev			0.09*** (0.01)	0.06*** (0.02)
Management as % of staff			-0.06*** (0.02)	-0.03 (0.02)
Adjunct instructors as % of instructors			-0.01** (0.01)	-0.00 (0.01)
Total distance programs			0.02*** (0.01)	0.02** (0.01)
Total certificate programs			0.04*** (0.01)	0.00 (0.01)
Institutional Indicators				
Public 4Yr				0.02 (0.35)
Cash flow ^c				0.12 (0.15)
End of year endowment ^c				0.35* (0.19)
Tuition as % of total rev				-0.01 (0.01)
Total student enrollment ^c				0.46*** (0.10)
N parameters	4	8	9	18
(-2) Log-likelihood	1140.14	877.40	1033.63	776.73
AIC	1158.14	911.40	1071.63	850.73
BIC	1159.36	915.84	1076.86	863.20
Chi-Square	1615.69	6766.62	6610.40	6867.30
Cox & Snell pseudo-R ²	0.69	0.71	0.70	0.71
Nagelkerke R ²	0.92	0.94	0.93	0.95

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

^b bachelor's is the comparison group^c measure is z-scored (SD = 1, Mean = 0)

the current model has refined our understanding of what factors drive the adoption of MOOCs.

Overall, Model D offers the greatest explanatory power of any model and is the best model with which to explain the patterns of MOOC adoption in the early years. In the following section, I briefly summarize results for Models A-C, but focus primarily on Model D for the main interpretation.

Model interpretation. Model A included only the main effects of time (AY 2011-12 through AY 2014-15). Each of the years was a significant predictor of MOOC adoption, which can be attributed to the fact that there were so few adopters relative to non-adopters. The difference between these two groups (adopters versus non-adopters) was going to be significant. When comparing the unconditional model (i.e., Model A that has no predictors), the logit coefficients when converted to probabilities (e.g. $\text{Probability} = 1/(1 + e^{-(\text{logit coefficient})})$) matched the probability of adoption in the life table (see Table 7, column of proportion of first adopters).

Model B included the effects of time in addition to the effects of two variables associated with prestige, which is the Carnegie Classification and admissions selectivity of the university. In this model, all time variables were significant. Although all time variables were negative, the third year provided the coefficient that was closest to 0 for all four-years, indicating the time in which adoption had the highest odds of occurring. When only prestige variables were in the equation, the estimated odds that research institutions adopted MOOCs compared to Bachelors were 19 times higher ($p < 0.01$, $e^{2.95}$) net of other predictors. Moreover, for each percent increase in selectivity, the estimated odds that an institution would adopt MOOCs were 4% higher ($p < 0.01$, $e^{0.04}$), controlling for other predictors. No other indicators were significant.

Model C included the effects of time in addition to the effects of select predictors of economic competition (grants and contracts as a percent of total revenue, managers as a percent

of total non-instructional staff, adjuncts as a percent of total instructional staff, number of distance education courses, and total number of certificates). According to the results of this model, time again was significant, with the highest odds of adopting MOOCs during the third year. Each of the main predictors was significant ($p < 0.05$) as well. Reliance on adjuncts and use of management were negative predictors. For example, when controlling for all else in the model, for each percent increase in management as a part of total staff, the estimated odds that an institution would adopt MOOC were 6% lower ($p < 0.01$, $e^{-0.06} = 0.94$). Similarly, for each percent increase in the percent of staff made up by adjunct faculty, the estimated odds that an institution would adopt a MOOC were 1% lower ($p < 0.05$, $e^{-0.01} = 0.99$). Yet there was a positive relationship for other components of economic competition. For each percent increase in revenue from private grants and contracts, the estimated odds that an institution would adopt a MOOC were 9% higher ($p < 0.01$, $e^{0.09} = 1.09$) net of all other predictors. Distance and certificate education were also positively associated with MOOC adoption. For a one program increase in distance programs, the estimated odds of adopting MOOCs were 2% higher ($p < 0.01$, where $e^{0.02} = 1.02$), while a one program increase in certificate programs increased the estimated odds of adopting MOOCs by 4% ($p < 0.01$, $e^{0.04} = 1.04$) when controlling for other predictors in the model.

Finally, model D included all the effects of Model B and Model C plus variables that were noted in the literature as predictors of diffusion of innovation such as wealth (e.g., cash flow and endowment) and institutional characteristics (e.g., whether or not the institution was public and a z-scored measure for total number of students enrolled).

According to Model D, there was some evidence that prestige and economic competition positively affected the odds of adoption. With regards to prestige, my results suggest that the

estimated odds were 3.5 times higher ($p < 0.01$, $e^{1.26} = 3.5$) that high-intensive research institutions (R1 or R2) compared to bachelor's-only colleges would adopt MOOCs. Also, for every 1% increase in selectivity, the estimated odds were 3% higher ($p < 0.01$, $e^{0.3} = 1.03$) that an institution would adopt a MOOC. With regard to economic competition, for every 1% increase in private grants and contracts as a percent of total revenue, the estimated odds that an institution would adopt a MOOC were 6% higher ($e^{0.06}=1.06$). For each additional distance education program offered, the estimated odds that institutions would adopt MOOC were 2% higher ($e^{0.02}=1.02$).

Some financial institutional characteristics were also positively associated with MOOC adoption, including the total amount of end-of-year endowment and student enrollment. These measures were both standardized, which means their effects were described in standard deviations (SD). Hence for every one SD increase in endowment, the estimated odds that an institution would adopt MOOCs were about 40% higher ($p < 0.10$, $e^{0.35}=1.41$), and for every one SD increase in enrollment size, the estimated odds that an institution would adopt a MOOC were almost 60% higher ($p < 0.01$, $e^{0.046}=1.58$). Still, it should be mentioned that the significance for endowments was only marginal ($p < 0.10$).

Each of the year variables was also significant. Like the hazard function also showed, AY 2013 (Year 3) remained the year in which MOOCs were most likely to be adopted. The coefficient, though negative, is the closest to 0 of all four-years.

In sum, what distinguished adopters from non-adopters was the research capacity of an institution, how selective it was, the percent of revenue coming in from private grants and contracts, as well as the size of its distance education programs, endowments, and student body. These results are largely consistent with the organizational change literature that argued that

slack resources and organizational size were strong predictors of institutional change (Berry & Berry, 2014; Cyert & March, 1963; Rogers, 1983). The new findings are that private contracts and grants and more distance education programs were positively associated with MOOC adoption, suggesting that expanding into the market via grants and contracts and distance education may be strong predictors of institutional change. While I used distance education as evidence of expanding into the nontraditional student market to make a profit, it may also be a strong predictor of MOOC adoption for other reasons. For instance, institutions that already offer a number of distance education programs may be more comfortable with offering distance education. There may be more buy-in from faculty, who are known to be very resistant to online education (Waks, 2016). In Walsh's study, buy-in from faculty at MIT and Berkeley made it much easier for the institutions to adopt the courseware. Institutions that offer a robust distance education program may also have a technical advantage, given the already existing technical infrastructure.

Section 2: The Motives of MOOC Adopters

The previous section on MOOC adoption established that prestige and, to some extent, economic competition were related to the initial adoption of MOOCs. In terms of prestige framework, both research capacity and selectivity mattered; in terms of economic competition, the percent of revenue from private grants and contracts and the extent to which the institution offers distance education programs were significant predictors of MOOC adoption. Institutional characteristics such as size of student population and endowment—the measures of the institution's capacity to innovate—were also evidence that the presence of institutional resources were important predictors of change. On this last point, the positive relationship between resources and adoption of a new program has already been well established in the literature

(Berry & Berry, 2014; Cyert & March, 1963; Rogers, 1983).

While Section 1 explored what drivers were most strongly associated with disruptive innovation controlling for time, it did not exploit the differences in adoption over time among the adopters themselves. However, because the extant literature on the adoption of an innovation has suggested that the mechanisms and motivations for adopting a new program or policy can vary over time among adopters, it is important to exploit these variations to achieve my purpose of understanding more about the process of disruptive innovation in higher education (Berry & Berry, 2014; Rogers, 1983).

There already exists some evidence that drivers of disruptive innovation differ by institutional type. Hollands and Tirthali (2014), in a study of 83 administrators, faculty members, researchers, and actors from 62 different institutions, found six different goals for why institutions adopted MOOCs:

1. extending the reach of the institution and access to education,
2. building and maintaining brand,
3. improving economics by lowering costs or increasing revenues,
4. improving educational outcomes for both MOOC participants and on-campus students,
5. innovation in teaching and learning, and
6. conducting research on teaching and learning.

These goals reflect different motives for adopting a disruptive innovation, where motives are the reasons for making a particular decision. Hollands and Tirthali's findings indicated that revenue generation and increasing efficiency are key motives for adopting MOOCs (e.g., Goals 2 and 3). They also showed that some institutions are interested in extending research on teaching and learning, which clearly aligns itself with prestige-building efforts, where research returns

dividends in prestige. Yet, the authors did not distinguish whether certain goals were more likely to be embraced by some types of adopters over others (e.g., public or private, elite or non-elite, etc.) because that was not part of their research design.

Walsh (2011) also found that revenue generation was a key motive for adopting open educational resources (OERs). In fact, the primary motive for most of the pioneers of OERs was to generate revenue (e.g., Fathom and AllLearn), and only a few institutions explicitly avoided revenue generation when they began experimenting with open educational resources (e.g., MIT's OCW and UC Berkeley's webcast.berkeley.edu).

Extent research has argued that pioneers of innovation are different from later adopters, and that earlier adopters of a new program or policy are more likely to be larger and with slack resources to absorb the cost and risk associated with innovation (Berry & Berry, 2014; Cyert & March, 1963; Mohr, 1969; Rogers, 1983). To understand whether institutions change and whether there is a difference in their motives, I employed a descriptive analysis of the 122 adopters to investigate variation in drivers over time as well as variation in whether the institutions partnered with for-profit providers compared to nonprofit providers. The research questions addressed in this section were:

- 2a. Does partnership with a for-profit versus nonprofit provider differ by economic competition or prestige-seeking behavior?
- 2b. Do these partnerships change over time? If so, how?

Empirical Approach

Given the small sample size of adopters, this model employed descriptive statistics only; that is, I did not use inferential (regression) analyses here. Regressions should have approximately 1,000 observations to have enough power to avoid Type I errors, given the

number of independent variables that I wanted to explore (Cohen, 1962, 1992). However, I still capitalized on the variation in the relationships by employing descriptive statistics (e.g., means testing) across the different indicators by whether an institution partnered with for-profit compared to nonprofit providers.

The outcome variable was a binary indicator variable for first-time affiliation with a for-profit or nonprofit provider (0 = nonprofit; 1 = for-profit provider) as a way to identify underlying motives of change. Partnerships with for-profits suggest a higher interest in profit making than institutions that partner with nonprofit providers. Independent variables included measures of prestige and measures of economic competition. I employed t-tests and chi-square to explore the statistical significance of the relationships. These tests are used when samples of first-time adopters are small and when the distribution is not known to identify whether a statistical difference between the groups exists (Shavelson, 1996). In my study, for instance, in the first year there were only 9 adoptions (e.g., three partnerships with nonprofit providers and six partnerships with for-profit providers). Readers should note that the findings presented here are substantively important, but they should interpret the descriptive statistics with caution. The group of first-time adopters by year was small, which means that any t-test or chi-square result reported could be reporting noise or, inversely, could not be picking up on an important difference simply because the sample size was not sufficient.

Results: The Relationship Between Drivers and Type of Provider on Average

Table 9 presents summary statistics for partnership with either a nonprofit versus for-profit provider by drivers of innovation. Specifically, it reports the means for relationships between the various mechanisms of innovation (e.g., prestige acquisition and economic competition and controls) and the types of providers (e.g., non-profit versus for-profit) for all

4 years. Results suggested that the type of provider choice (e.g., with a for-profit or nonprofit provider) did vary by the mechanisms of innovation. There were many more first-time partnerships with for-profit providers ($n = 95$) than nonprofit providers ($n = 27$). Overall, institutions that partnered with for-profit providers were comprised of fewer research institutions ($p < .05$), were less selective ($p < .01$), and were more dependent on tuition as a percent of their total revenue ($p < .05$). More public institutions than private institutions partnered with for-profit providers as well ($p < .05$).

Table 9. Associations Between Providers and Mechanisms of Change

	Non-Profit (n=27)	For-Profit (n= 95)
<i>Prestige Acquisition</i>		
Carnegie *		
Research (%)	74.07 (44.66)	69.47 (46.30)
Masters (%)	3.70 (19.25)	17.89 (38.53)
Bachelors (%)	22.22 (42.37)	7.37 (26.26)
Religious/Other (%)		5.26 (0.22)
Admissions selectivity**	61.69 (24.91)	45.69 (22.69)
<i>Economic Competition</i>		
Private contracts/grants as % of total rev	3.70 (4.04)	3.60 (4.70)
Management as % of staff	8.72 (4.75)	9.17 (5.17)
Adjunct instructors as % of instructors	11.09 (11.99)	13.45 (14.36)
Total distance programs	7.93 (14.37)	9.21 (15.32)
Total certificate programs	14.74 (29.08)	11.8 (20.16)
<i>Institutional Indicators</i>		
Public 4Yr (%)*	37.04 (49.21)	60.00 (49.25)
Cash flow (Millions)	161.51 (532.56)	152.26 (470.85)
End of year endowment (Billions)	3.01 (6.01)	1.64 (4.56)
Tuition as % of total rev*	30.02 (17.16)	40.57 (21.90)
Total student enrollment	19660 (15840)	20984 (14585)
Standard errors in parentheses *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$		

There was very little evidence of variation in economic competition and provider type

since none of the relationships were significant and the values did not change much. For example, institutions that partnered with for-profit providers on average offered 9.21 distance education programs compared to 7.93 for institutions that partnered with nonprofit providers. The differences were most stark in the prestige indicators and the institutional indicators that reflected the institution's average capacity to innovate.

Results: The Relationship Between Drivers and Type of Provider Over Time

This section presents the main findings for this analytic section to show to what extent drivers and institutional capacity changed over time for institutions that partnered with for-profit compared to nonprofit providers. I disaggregated these data by drivers and institutional capacity by provider type over 4 years since the literature has suggested that institutional types change over time (Berry & Berry, 2014; Rogers, 1983). For example, Rogers broke diffusion into five types of adopters based on the progression of time in this order: innovators, early adopters, early majority, late majority, and laggards. Characteristics such as size, wealth, political power, and so on then further distinguished these types of innovators.

Table 10 reports on the overall differences in the characteristics of first-time adopters over the 4 years without taking into account differences in whether institutions partner with a for-profit or a nonprofit provider. Compared to adopters in AY 2014-15, pioneers that adopted MOOCs in the first year AY 2011-12 and early adopters that adopted MOOCs in AY 2012-13 were more often research institutions and with more selective admissions. For example, the pioneers rejected about 77% of their applicants, while the adopters in year 2014-15 rejected only 42% on average. There were no striking changes over the 4 years for the variables that measure how aggressive the institutions were in the market. Yet, like the prestige indicators, for every year that passed, new adopters showed they had less capacity to innovate compared to the year

before. For instance, the average endowment size of adopters in AY 2011-12 was \$6.84 billion; by the last year of adoption, the average institutional endowment size was \$721 million. Tuition revenue comprised only 15% of institutional core revenue for pioneers, but almost 40% of total core revenue for institutions that adopted in AY 2014-15.

These differences can be broken down further by institutions that partner with either a for-profit versus nonprofit provider. I show these differences in the following table, Table 11. It is this table that ultimately shows possible correlations between institutional characteristics and institutional motives that no other study on the adoption of MOOCs has investigated.

Table 10. Adopter Characteristics Over Time

	2011 (n=9)	2012 (n=28)	2013 (n=49)	2014 (n=36)
<i>Prestige Acquisition</i>				
Carnegie				
Research (%)	100.00 (0.00)	89.29 (31.50)	63.27 (48.71)	58.33 (50.00)
Masters (%)		3.57 (18.90)	22.45 (42.16)	16.17 (37.80)
Bachelors (%)		3.57 (18.90)	12.24 (33.12)	16.67 (37.80)
Religious/Other (%)		3.57 (18.90)	2.04 (14.29)	8.33 (28.03)
Admissions selectivity	77.42 (16.87)	58.72 (21.42)	44.06 (22.40)	41.83 (22.79)
<i>Economic Competition</i>				
Private contracts/grants as % of total rev	2.54 (1.48)	6.94 (6.50)	2.82 (3.73)	2.42 (2.81)
Management as % of staff	6.94 (3.11)	9.61 (5.15)	9.07 (5.14)	9.20 (5.33)
Adjunct instructors as % of instructors	12.50 (11.97)	8.56 (8.03)	14.03 (13.51)	14.93 (17.61)
Total distance programs			12.31 (16.74)	13.50 (16.69)
Total certificate programs			20.02 (27.82)	14.94 (20.34)
<i>Institutional Indicators</i>				
Public 4Yr (%)	44.44 (52.70)	57.14 (50.40)	48.98 (50.51)	63.89 (48.71)
Cash flow (Millions)	1131.64 (1117.75)	-11.61 (271.90)	104.96 (277.25)	106.17 (291.06)
End of year endowment (Billions)	6.84 (6.62)	3.14 (5.75)	1.25 (3.16)	0.72 (1.54)
Tuition as % of total rev	15.55 (13.43)	31.62 (15.75)	45.33 (22.70)	39.39 (19.88)
Total student enrollment	22942 (13785)	26687 (16801)	19583 (14662)	16971 (12520)

Table 11. Characteristics of First-time Adopters by Provider Type for AY 2011-AY 2014 (n = 122)

	2011			2012			2013			2014	
	Non-Profit (n=3)	For-Profit (n=6)		Non-Profit (n=5)	For-Profit (n=23)		Non-Profit (n=9)	For-Profit (n=40)		Non-Profit (n=10)	For-Profit (n=26)
Prestige											
Research (%)	100.0	100		100	86.96 (34.44)		66.67 (50.00)	62.50 (49.03)		60.00* (51.64)	57.69* (50.38)
Masters (%)					4.35 (20.85)		11.11 (33.33)	25.00 (43.85)			23.08 (42.97)*
Bachelors (%)					4.35 (20.85)		22.22 (44.10)	10.00 (30.38)		40.00* (51.64)	7.69* (21.17)
Religious/Other (%)					4.35 (20.85)			2.50 (15.81)			11.54* (32.58)
Admissions selectivity (%)	74.91 (24.03)	78.68 (14.79)		54.7 (34.91)	59.6 (18.36)		58.23** (23.03)	40.87** (21.26)		64.32*** (23.36)	33.18*** (15.82)
Economic Competition											
Private contracts/grants as % of total rev	3.64 (0.46)	2.00 (1.52)		4.17 (1.42)	7.55 (7.03)		5.52 (6.40)	2.21 (2.58)		1.84 (1.60)	2.64 (3.16)
Management as % of staff	7.21 (1.84)	6.80 (3.75)		10.49 (5.09)	9.42 (5.25)		7.63 (5.91)	9.39 (4.98)		9.29 (4.22)	9.16 (5.78)
Adjunct instructors as % of instructors	17.40 (13.85)	10.05 (11.45)		8.14 (9.94)	8.66 (7.82)		9.63 (9.85)	15.02 (14.12)		11.98 (14.89)	16.06 (18.70)
Distance programs							9.67 (12.26)	12.90 (17.66)		12.70 (19.47)	13.81 (15.91)
Certificates programs							23.89 (38.61)	19.15 (25.34)		18.30 (28.79)	13.65 (16.56)
Institutional Indicators											
Public 4Yr (%)	33.33 (57.74)	50.00 (54.77)		60.00* (54.77)	56.52* (50.69)		33.33* (50.00)	52.50* (50.57)		30.00** (48.30)	76.92** (42.97)
Cash flow (millions)	505.1 (990.9)	1444.9 (1119.3)		-287.9 (577.8)	48.4 (94.4)		118.7 (160.6)	101.9 (298.7)		321.7*** (498.0)	23.3*** (60.1)
End of year endowment (billions)	3.79 (5.19)	8.36 (7.14)		7.17 (13.21)	2.26 (2.08)		1.54 (1.27)	1.19 (3.46)		2.02 (2.52)	0.22 (0.29)
Tuition as % of total rev	19.72 (22.79)	13.47 (8.07)		35.47 (9.50)	30.79 (16.85)		33.54* (20.85)	47.98* (22.49)		27.21* (15.37)	44.08* (19.65)
Total student enrollment	15482 (16044)	26672 (12288)		25839 (15176)	26871 (17446)		21793 (17101)	19086 (14255)		15903 (16064)	17382 (11222)

*** p<0.001, ** p<0.01, * p<0.05 Statistical tests are done by year. Standard errors in parentheses.

Table 11 reports the average characteristics of first-time adopters for AY 2011-12 to AY 2014-15 for institutions that partner with for-profit versus nonprofit providers. Indeed, first-time adopters that partnered with for-profit providers were different from those that partnered with nonprofit providers. In each year, there was a new group of first-time adopters that either partnered with a for-profit or nonprofit provider. Figure 4 presents the plots of the indicators to highlight the differences in mechanisms of innovation by for-profit and nonprofit providers over time.

Initially, there was no statistically significant difference between institutions that partnered with for-profit or nonprofit providers in AY 2011-12 in terms of Carnegie ranking or selectivity, but there were significant differences in AY 2014-15. Regarding Carnegie classifications, in AY 2011-12, 100% of institutions that partnered with for-profit providers and nonprofit providers were research institutions. But by AY2014-15, while 57% of new adopters with for-profit providers were research institutions, the other new adopters were primarily from non-elite tiers. Table 11 shows the greatest increase of adopters came from Religious/other schools that conducted no research. There was also a 3-percentage point decrease in the number of Bachelor's degree-granting institutions. By contrast, approximately 60% of institutions that partnered with non-profit providers were research, while the other 40% were exclusively Bachelors-awarding institutions.

A similar pattern occurred with admissions selectivity. In AY 2011-12, institutions that partnered with either a nonprofit and for-profit provider had about the same rejection rates on average (e.g., 75% to 79%, respectively). However, by AY 2014-15, new adopters that chose to partner with for-profit providers were much less selective than their counterparts who partnered with nonprofit providers (e.g., 33% compared to 66%).

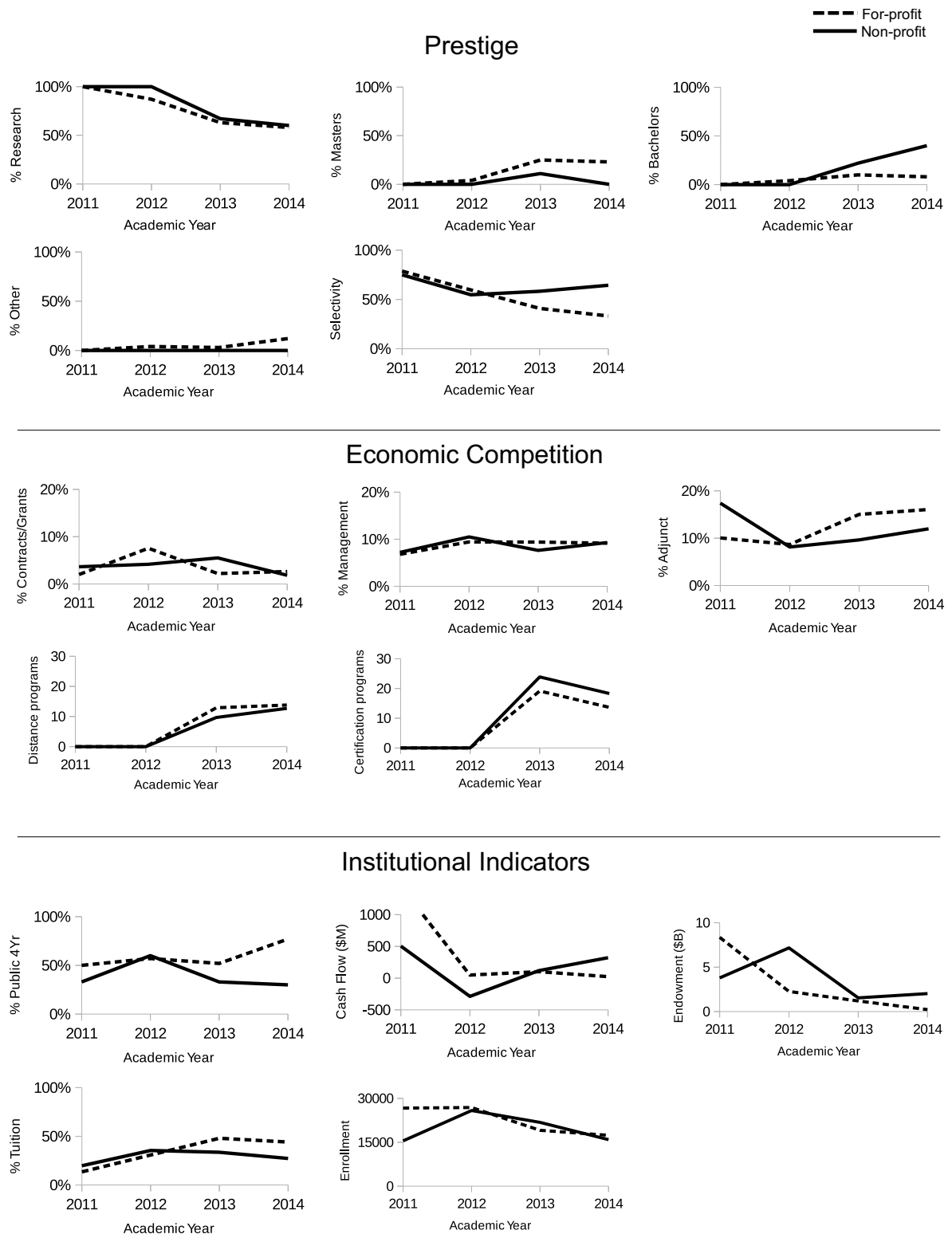


Figure 4. Differences in characteristics of first-time adopters by provider type over time

Significant differences in institutional capacity were also observed. On average, for every year that passed, first-time adopters that partnered with for-profit providers showed less capacity to innovate compared to their nonprofit counterparts. For instance, the number of public colleges and universities that partnered with for-profit providers increased annually, while the number of publics that partnered with nonprofit providers monotonically decreased after 2012 (see Figure 4). Similarly, for each year that passed, the average endowment of first-time adopters that partnered with for-profit providers decreased dramatically. The average endowment for an institution that partnered with a for-profit dropped to 2.2 million by AY 2014-15, from a height of 83.6 in AY 2011-12. In comparison, while endowments were higher for institutions that partnered with nonprofits in the first years, they were still relatively high in the latter year of adoption. Moreover, the size of endowments for institutions that partnered with nonprofits was always higher than the institutions that partnered with for-profits for every year except the first year (AY 2011-12).

Finally, for each year that passed, new adopters that partnered with for-profit providers showed greater reliance on tuition for revenue compared to institutions that partnered with nonprofit providers. In AY 2011-12 and AY 2012-13, the average amount of revenue that came from tuition was fairly similar for institutions that partnered with for-profit versus nonprofit providers (e.g., 20% compared to 13%). However, by AY 2014-15, first-time adopters that partnered with for-profit providers received about 44% of their total core revenue from tuition on average, while first-time adopters that partnered with nonprofit providers only received about 27% of their revenue from tuition.

Differences in economic competition were not particularly informative. There were only minor changes over time for institutions that partnered with for-profits compared to nonprofits

and no difference between the two groups was ever statistically significant. Although the number of distance education programs was significant in the first model, there was little evidence that the number of distance education programs correlated with the institution would partner with for-profit compared to nonprofit providers. Distance education and certificates had zeros for the first 2 years (AY 2011-12 and AY 2013-14) because IPEDS did not collect data on these two dimensions until AY 2013-2014.

Collectively, what these findings suggest is that patterns of adoption among the adopters were not uniform over time or type of institution. For each year that passed, new adopters that partnered with for-profits compared to nonprofit providers were less prestigious and exhibited lower capacity to innovate. In comparison, institutions that partnered with nonprofit providers tended to be more prestigious and have more slack resources to innovate. Additionally, the results showed that there was larger and more rapid growth in partnerships with for-profit providers compared to nonprofit providers. This may suggest that revenue generation was a key motivator of institutional adoption of MOOCs and it may have become a more central motivation for each year that passed as the average institutional capacity to innovate of first-time adopters became more and more constrained.

Section 3: Latent Class Analysis of Institutional Innovators

According to the results in Section 1, prestige and economic motivation were important predictors of change. Also, the hazard plot showed that the rate of adoption was not constant, suggesting that various mechanisms of diffusion may have induced adoption by institutions at different times. The DTHM, however, was not designed to distinguish among actors in a group, just between groups (i.e., it explains why some institutions “experienced the event” while others

did not). The DTHM does not provide an explanation for if and why there are differences among the adopters themselves.

In Section 2, I examined partnerships with for-profit and nonprofit providers by drivers over time. The outcome variable was partnership with a for-profit or nonprofit provider. The results of this analysis suggested drivers of adopters indeed changed over time. Specifically, before the peak year AY 2013-14, adopters in AY 2011-12 and 2012-13 were more prestigious, with fewer characteristics associated with economic competition, and adopters in 2013 and 2014 were less prestigious and more financially unstable. The combined result of the first and second models is that institutional adoption of MOOCs was not uniform. This implies that there exist different combinations of prestige-seeking, economic competition as well as institutional capacity to innovate (e.g., public, slack resources, size). Looking at the adopters over time brought out these differences.

Because the results suggested that adopters cannot be viewed as a monolithic group of innovators or be readily described based on their prestige-seeking behavior, economic competition, or other general indicators of institutional innovation, a natural next step is to assess the extent to which institutions can be classified according to combinations of the indicator variables. The research questions therefore addressed in this section were:

- 3a. To what extent does a typology of institutional innovators based on prestige-seeking behavior and economic competition exist?
- 3b. To what extent does this typology of innovators relate to MOOC adoption?
- 3c. How does the adoption of innovation by institutional subgroup vary over time?

Empirical Approach

This study employed a latent class analysis (LCA) to examine the extent to which a typology of innovators exists in 4-year colleges. LCA is a subset of mixture modeling that is used to determine the extent to which there exists an unobserved (latent) categorical variable that divides a population into mutually exclusive latent classes (Jung & Wickrama, 2008; Lanza & Rhoades, 2013; Lazarsfeld et al., 1968). LCA is useful for identifying homogeneous subpopulations within the larger heterogeneous population and for identifying meaningful groups or classes of individuals (Jung & Wickrama, 2008). Moreover, while LCA is often viewed as a type of clustering analysis, where the model focuses on the structure of the variables, that perspective is incorrect. In an LCA, the focus is on the cases (Samuelson & Raczynski, 2013, p. 306) and can be described as institution-centric in this case. In my study, the LCA therefore focused on the groups of institutions classified according to the drivers of institutional innovation.

The different subgroups were based on the indicators I employed in the first two sections. To the extent any subgroups of innovators were identified, they were determined based on the theoretical construct of this dissertation; that is, economic competition and prestige as well as other key institutional characteristics influenced innovation habits of any given institution and furthermore, institutions were driven by a combinations of these factors. The specific indicators that were used were: Carnegie Classification, selectivity, percent of revenue generated from private grants and contracts, mid- and senior-level managers as percent of total staff, adjuncts as percent of total teaching staff, total number of distance education programs, and total number of certificate programs. The model also incorporated the confounding variables: public, cash flow, end-of-year endowment, tuition as percent of revenue, and total student enrollment.

The LCA requires binary variables for the input, and so each of these variables was

turned into a binary indicator variable for above or below the median, where high indicates above the median (1 = above the median, 0 = below the median): high selectivity, high percent private grants and contracts, high management, high adjuncts, high distance education, high certification programs, high cash flow, high endowment, high tuition as a percent of total revenue, and high enrollment. The Carnegie Classification was collapsed into a binary variable with research institutions coded 1 and non-research coded 0. Public remained the same (1 = public, 0 = private).

Statistical procedures were all done in Mplus, version 7.4 (Muthén & Muthén, 2012). All variables were entered using a three-step LCA procedure with an auxiliary command DCAT. This procedure allowed the indicator variables to determine the number of statistically differently motivated universities and colleges, and then it subsequently tested the relationship between the subgroup of innovators and the likelihood of adopting a MOOC (Asparouhov & Muthén, 2014). Each college and university was then assigned to the most likely class. Then I conducted an auxiliary command (DCAT), a chi-square testing procedure to examine the relationship between the latent predictor (i.e., the Class) and the manifest outcome (e.g., MOOC adoption) to produce a distal outcome (e.g., the relationship between the classes and MOOC adoption) (Asparouhov & Muthén, 2014; Lanza et al., 2013). See Chapter 3 for more details on the LCA procedure.

Empirical Results

Indicators of model fit. This section presents the results for the LCA, which assessed the extent to which different types of motivated institutions exist. First, I present the model fit information, then I present the subgroup analysis that includes the indicator plot, followed by the distal outcome analysis.

Table 12 reports model fit statistics, including the Lo-Mendell-Rubin (LMR) and the

adjusted Bayesian Information Criterion (BIC), which are important indicators of the final number of classes (Nylund et al., 2007). For each model, the best log likelihood was replicated, indicating that the model had converged around the lowest value and the model had been statistically identified; that is, the expectation-maximization (EM) algorithm had found the maximum likelihood of parameters in the statistical model, which was dependent on latent variables (Dempster et al., 1977).

The usual likelihood ratio chi-square test (2 times the log likelihood difference) should not be used to test a $k-1$ versus k class model, because 2 times the log likelihood difference is not chi-square distributed in this mixture models (Asparouhov & Muthén, 2014; Nylund et al., 2007). To generate the Lo Mendell Rubin (LMR) statistic, I used TECH 11 in Mplus. According to Asparouhov and Muthén (2012), TECH11 uses the correct distribution of 2 times the log likelihood difference to perform this test, which is obtained by the k class run also doing a $k - 1$ class analysis and using the derivatives from both models to compute the p-value. A low p-value rejects the $k - 1$ class model in favor of the k class model.

Another indicator that has shown to be consistently powerful in distinguishing the k from the $k - 1$ number of classes is the Bootstrap Likelihood Ratio Test (BLRT), which is generated using TECH14 in Mplus (Asparouhov & Muthén, 2012). For LCA models, the BLRT has better accuracy for correctly identifying the number of classes (Nylund et al., 2007). However, even after using the recommended number of draws (100) (Asparouhov & Muthén, 2012; Bowers & Sprott, 2012), Mplus was unable to replicate the best log likelihood for the 8-, 7-, 6-, and 5-class models. According to Nylund et al. (2007), the LMR and BLRT for a finite mixture model are similarly accurate; they suggest that once the first time the p-value of the LMR is nonsignificant, it is a good time to stop increasing the number of classes. For these reasons, I included only the

LMR results in Table 12 and stopped once the LMR became nonsignificant at the 8-class model.

Determining the number of subgroups requires both quantitative and qualitative interpretation. The model must be both statistically sound and qualitatively interpretable (Nylund et al., 2007) and the literature considers no one method the best way to indicate the proper number of classes (Graves & Bowers, in press). To find the best model fit, I ran the LCA on a two-class model, running subsequent models until both the BIC and LMR statistics indicated the best model fit (Graves & Bowers, in press; Jung & Wickrama, 2008).

Table 12. LCA Results and Fit Statistics for Types of Innovators

Model	AIC	BIC	(-) Log Likelihood	LMR (adj) Test for k-1 classes	<i>p</i>	Entropy
Two Classes	21727.061	21859.387	-10838.531	1932.226	0.000	0.842
Three Classes	20972.968	21174.103	-10448.484	771.951	0.000	0.899
Four Classes	20440.653	20710.597	-10169.326	552.488	0.000	0.903
Five Classes	19957.987	20296.740	-9914.994	503.357	0.000	0.902
Six Classes	19835.454	20243.010	-9840.727	146.983	0.000	0.906
Seven Classes	19775.720	20252.092	-9797.860	84.839	0.030	0.870
Eight Classes	19756.818	20301.999	-9775.409	44.433	0.638	0.877

According to the literature on using the LMR test (Lo, Mendell, & Rubin, 2001), the LMR became statistically non-significant at the 8-class model ($p > .05$), which indicated that the 7-class model was the best fit. However, the first positive change in BIC occurred at the 7-class model (BIC = 20252.09 for the 7-class model, compared to 20243.01 for the 6-class model), making the 6-class model the best fit. Entropy, the ability to distinguish strongly between classes, was high for classes 2 through 6. Another indicator of model fit is the classification probabilities, shown in Table 13 (Graves & Bowers, in press; Lanza & Rhoades, 2013). While class 6 had strong classification probabilities, one of the classes had fewer than 4% of the population, suggesting over-identification of classes. Thus, after careful examination of the different

subgroups and fit statistics, I selected the 5-class model instead of the 6-class model.

Deciding on a smaller number of classes is a conservative approach some researchers employ when there is mixed evidence that the number of classes might be higher, but smaller classes are more convincing (Bowers & Sprott, 2012; Graves & Bowers, in press; Lanza & Rhoades, 2013). Selecting fewer classes is more conservative in the event that the model over-identified the number of classes. Compared to the 6-class model, the 5-class model was more easily identified, had greater parsimony, and the parameters had solutions that could be interpreted. That is, the 5-class model showed more logical patterns that were distinct from each other and could be easily labeled (Nylund et al., 2007; Tofghi & Enders, 2008). Finally, the classification probabilities for the 5-class model are presented in Table 13, showing strong results across the diagonal (e.g., all probabilities are above 90%).

Table 13. Classification Probabilities for the Most Likely Class Membership

Latent Class	Most Likely Latent Class Membership				
	Class 1 (Opportunists)	Class 2 (Wealth Managers)	Class 3 (Pragmatists)	Class 4 (Innovators)	Class 5 (Stalled)
Class 1	0.919	0.034	0.007	0.013	0.027
Class 2	0.045	0.918	0.000	0.001	0.036
Class 3	0.006	0.000	0.942	0.030	0.021
Class 4	0.007	0.001	0.031	0.961	0.000
Class 5	0.025	0.012	0.005	0.000	0.957

Five latent subgroup results. I identified five significantly different subgroups of institutions. Based on the unique qualities of each subgroup that are shown in Table 14, I assigned the following labels to each subgroup: (1) Opportunists, (2) Pragmatists, (3) Wealth Managers, (4) Accelerators, and (5) Laggards. Figure 5 shows the indicator plot for the proportions of the indicator variables per subgroup of institutions, and Table 14 shows the

probabilities for each group by mechanisms of innovation. Each latent class corresponds to an underlying subgroup of institutional innovators. Calling this a typology of institutional innovators is intentional on my part. Findings from Sections 1 and 2 provide evidence that certain institutions are more or less likely to innovate based on their composition of drivers and capacity to innovate. By employing an LCA, I used observable data to test the extent to which a latent class of innovators exists. Because the model converged, I can say with statistical confidence there are at least five different types of “innovators,” or groups of institutions characterized by their drivers and capacity to innovate.

Table 14. Probabilities of Mechanisms of Innovation by Group

Variable	Opportunists (18%)	Wealth Managers (17%)	Pragmatists (21%)	Accelerators (15%)	Laggards (30%)
High research capacity	0.18***	0.01	0.05***	0.89***	0.00
High selectivity	0.40***	0.58***	0.46***	0.60***	0.50***
High private contracts and grants	0.48***	0.39***	0.62***	0.96***	0.25***
High management	0.58***	0.61***	0.24***	0.29***	0.68***
High adjunct	0.67***	0.33***	0.50***	0.34***	0.57***
High distance education programs	0.66***	0.04*	0.55***	0.75***	0.34***
High certification programs	0.74***	0.20***	0.54***	0.82***	0.29***
Public	0.02	0.00	1.00	0.79***	0.03
High cash flow	0.92***	0.94***	0.13***	0.71***	0.16***
High Endowment	0.73***	1.00	0.20***	0.97***	0.06*
High tuition	0.97*	0.46*	0.11***	0.03*	0.75*
High enrollment	0.87***	0.05	0.83***	1.00	0.04*

*** p<0.001, ** p<0.01, * p<0.05

The Opportunists made up about 18% of the institutions. Many institutions in this group rely on adjunct faculty (67%), offer more distance education (66%), and produce more certificate programs (74%) than the median institution in the sample. Most of the institutions in this group are wealthy, with above median enrollments (87%), high cash flow (92%), and big endowments

(73%). Based on the evidence, this group had resources to support their students by discounting tuition more, but opted instead to be more economically competitive. Hence, their activities signaled opportunistic behaviors or putting institutional self-interests first. Examples of institutions in this group include University of San Francisco in California, Pratt Institute in New York, and Bethel University in Minnesota.

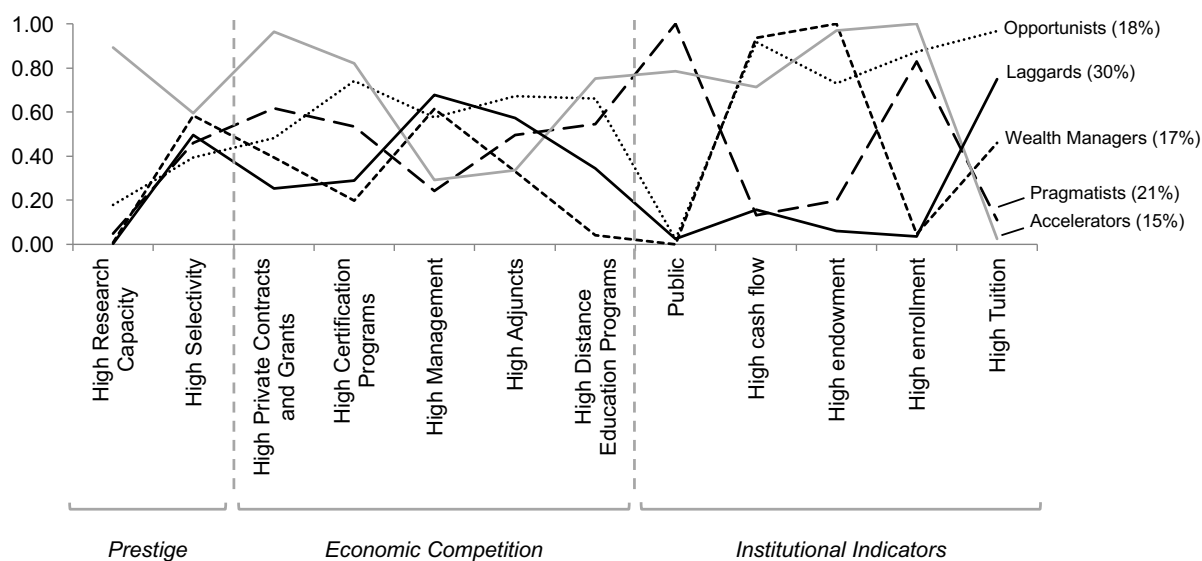


Figure 5. Statistical indicator plot

In comparison, the Pragmatists, which made up 21% of the group, are more diversified in terms of economic competition but also more attentive to student needs. For example, a relatively high proportion of the institutions had an above average amount of revenue coming from private grants and contracts (62%) and some deployed more distance education (55%) and certificate programs (54%) compared to the median. Some institutions also relied heavily on adjuncts, but only 50%. Yet, most institutions in this group were not very dependent on student tuition (89%). This group exhibited not only a practical pursuit of the market, but also a practical approach to helping their students contain costs and keeping quality up if we used dependence on adjunct, part-time faculty as a measure of quality (see Waks, 2016). All the institutions in this

group were public status institutions, which means that tuition was state subsidized. State subsidies may, in part, explain their lower dependence on student tuition for revenue. Examples of institutions in this group include SUNY College at Potsdam in New York, Emporia State University in Kansas, and University of Hawaii at Hilo.

Another group called the Wealth Managers made up about 17% of the sample. These institutions are all well-endowed with positive financial slack, as measured by their cash flow outcomes (94%). But they are also above the median in terms of the proportion of mid-level and senior-level managers out of total staff, compared to other institutions in the sample. Specifically, 66% of institutions in this group were in the high-management group. They were otherwise characterized by little else in terms of prestige or economic competition. For instance, these institutions did not offer a lot of distance education or certificate programs relative to the other institutions in the sample nor were they particularly research-intensive or selective. The evidence suggests these institutions were interested in building and sustaining wealth through reliance on managers and keeping it contained. Examples of institutions in this group include Wheaton College in Massachusetts, Colgate University in New York, and Spelman College in Georgia.

The Accelerators, which made up 15% of the sample, are extremely prestigious and economically competitive in strategic areas. Almost all are research institutions (89%) and are the most selective of any class. For example, 60% of institutions are above the median in terms of selectivity, where most other classes have only 40-50% of institutions with high selectivity. The Accelerators got their name from the fact that 75% of the institutions in this group offer an above average number of distance education programs and 82% of the institutions offer an above average number of certificate programs. According to the results, more than any other group of institutions, the Accelerators contained the highest percentage of institutions to offer above the

median in terms of distance education and certificate programs. For example, on average, 66% of Opportunists offered above the median in distance programs, while only 33% of the Laggards provided above the median in distance education programs. These findings suggest that the Accelerators compared to their peers were more “innovative” since distance education and certificates are perceived as educational innovations, given that they allow for increased access from nontraditional students (Baum et al., 2013; Christensen & Eyring, 2011; Lederman, 2016).

Moreover, while the Accelerators may offer more distance education and certificate programs, they are not necessarily aggressively market-oriented. For instance, though they delivered education in new ways, which could be perceived as both innovative *and* market-oriented, these institutions were not market-oriented in areas that are known to compromise quality of student education. That is, compared to their peer groups, the Accelerators were light on managerial capacity and dependence on adjunct faculty. This means that the Accelerators have not focused on extended managerial capacity, which, according to Slaughter and Rhoades (2004), is used to streamline campus efficiencies. These types of efficiencies are reflective of more business-like practices on campus that ostensibly shake the pillars of a liberal arts education by eliminating programs that are not self-sufficient or considered efficient (Slaughter & Rhoades, 2004; Zusman, 2005). Also, the Accelerators compared to their peers did not cut costs by using adjunct faculty rather than tenure or tenure-track faculty, which many researchers have speculated compromise the institutional quality of education. Ron Ehrenberg (2012), an economist of higher education, noted that a tenure-track system provides senior faculty with job security, which then incentivizes faculty members to share their experience with junior colleagues and students without creating competitors who want to challenge their position. Ehrenberg further contended that tenure-track positions facilitate intergenerational transmission

and expansion of knowledge that otherwise are not achieved if tenure track does not exist (Ehrenberg, 2012). For these reasons, I posit that the Accelerators are “strategic” in how they orient themselves to the market. While they may be extending their reach into new markets, they are not participating in practices that have been shown to compromise educational quality. Examples of institutions in this group include Georgetown University in DC, Clark University in Massachusetts, the University of California at Santa Barbara, and Princeton University in New Jersey.

Finally, the last group is the Laggards, which made up the largest percentage of institutions (30%). The major distinguishing features of this group are their high reliance on mid- and senior-level managers (68%) and tuition as the biggest component of their revenue (75%). This group is the most under-resourced of all. Institutions in this group are not well endowed nor do they have a lot of cash leftover after balancing revenues with expenditures. Most schools do not offer many distance education or certification programs compared to their peers. Finally, they suffer from small enrollments, which is a major source of income for institutions. This means that the students are responsible for financially supporting these institutions through student tuition. In sum, the evidence suggested these schools were falling behind in terms of getting their costs under control and increasing access compared to the other institutions in the sample. Examples of institutions in this group include Lakeland College in Wisconsin, Brevard College in North Carolina, and York College in Nevada.

These five classes are statistically distinct from each other. They reflect different degrees of being motivated by prestige versus economic competition as well as different degrees of being limited or assisted by institutional capacity. These findings suggested that institutional innovation in higher education may be better explained using competing motivations rather than

coarse categorization that typify research on higher education, such as comparing high research to Bachelors, public to private, or selective to non-selective.

Results for Distal Outcome

The results for the LCA using the three-step approach for the adoption of MOOCs by group (the distal outcome) are presented in Table 15 (Asparouhov & Muthén, 2014) and the significance levels of the difference between the groups are presented in Table 16. The ability to predict a distal outcome from latent class membership provides information about how the combination of characteristics, behaviors, or both predict an outcome of interest (Lanza et al., 2013). Analysis of the distal outcome provides a model-based approach to testing for mean differences across subgroups on an outcome variable – in this case, MOOC adoption. Of the Accelerators 38.1% adopted a MOOC, which was by far the largest average ($p < 0.001$). In comparison, only 0.90 % of the Laggards adopted MOOCs. On average, 3 to 5% each of the Wealth Managers, Opportunists, and Pragmatists adopted MOOCs. These findings suggested there is a wide gap in the experimentation and adoption of a disruptive innovation between the Accelerators and the other subgroups. However, there was no statistically detectable difference between Wealth Managers, Pragmatists or Opportunists ($p > 0.05$). Laggards statistically adopted MOOCs less than any other group ($p < 0.05$).

Table 15. Probabilities of Adopting a MOOC by Group

	Prob	S.E.	Odds Ratio	S.E.	2.5% C.I.	97.5% C.I.
Opportunists	0.059	0.017	6.511	3.939	1.989	21.313
Wealth Managers	0.043	0.015	4.715	2.957	1.379	16.118
Pragmatists	0.033	0.011	3.606	2.189	1.097	11.848
Accelerators	0.381	0.038	64.395	34.210	22.732	182.417
Laggards	0.009	0.005	1.000	0.000	1.000	1.000

Table 16. Statistical Significance Between Groups

	Chi-Square	P-Value	Degrees of Freedom
Overall test	110.458	0.000	4
Accelerators vs. Opportunists	57.757	0.000	1
Accelerators vs. Pragmatists	79.297	0.000	1
Accelerators vs. Wealth Managers	69.319	0.000	1
Accelerators vs. Laggards	96.610	0.000	1
Opportunists vs. Pragmatists	1.514	0.219	1
Opportunists vs. Wealth Managers	0.398	0.528	1
Opportunists vs. Laggards	7.273	0.007	1
Pragmatists vs. Wealth Managers	0.286	0.593	1
Pragmatists vs. Laggards	4.202	0.040	1
Wealth Manager vs. Laggards	4.547	0.033	1

Figure 6 presents the early trends of adopting a MOOC by LCA subgroup from AY2011-12 to AY 2014-15. This figure depicts the relative innovativeness of the Accelerators compared to any of the other classes of innovators. The Accelerators, the smallest subgroup of institutions, not only adopted the most MOOCs but also consistently adopted more MOOCs than any other class over the 4 years analyzed in the study. The figure also highlights how the Opportunists peaked in 2013, but then experienced a sharp decline in AY 2014-15, providing evidence that the Opportunists were a more transient group of innovators compared to the others. The Wealth Managers, Pragmatists, and Laggards show characteristics of being less innovative compared to the Accelerators, although their growth continued on a slow positive trajectory, even when the Accelerators sharply reduced their adoption after AY 2013-14. Nevertheless, it should be noted that although my data capture the greatest number of years thus far compared to other studies, the diffusion of this innovation is ongoing. As the patterns continue to unfold over time, we may

see all the innovations converge at a certain point in time.

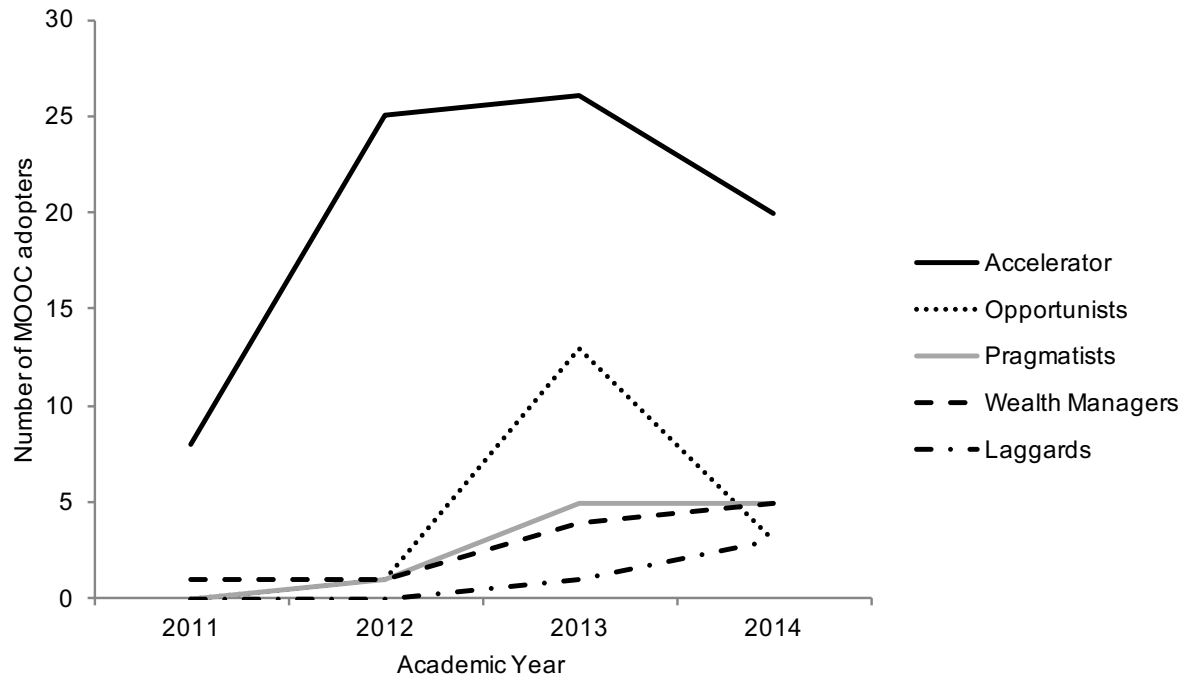


Figure 6. MOOC adoption by group from AY 2011-12 to AY 2014-15

Chapter 5: Discussion & Conclusion

Review of Study

There is growing interest in using disruptive innovations to bring down costs and increase access to high-quality, affordable education (Bowen, 2015; Carey, 2015; Christensen & Eyring, 2011; Selingo, 2013). A disruptive innovation is an innovation that saves students time and money (Christensen & Horn, 2013). Despite the growing political and economic pressure to disrupt higher education, the prevailing perception of higher education is that it remains highly resistant to change (Diamond, 2006; Kirschner, 2012). Others have argued that in fact higher education is innovative, but only small segments of it, which often go unobserved (Kezar, 2014; Meyer & Rowan, 2006). Despite these contradictory beliefs about higher education, there is very little empirical and conceptual research on the systematic adoption of a disruptive innovation across a wide variety of schools. The purpose of this dissertation was to add to our understanding of how disruptive innovation takes place across a wide variety of institutions.

This dissertation was grounded broadly in a policy diffusion framework (Berry & Berry, 2014). According to this framework, internal determinants (e.g., endogenous social, political, and economic institutional attributes) plus mechanisms of diffusion (e.g., competition) can be used to explain the adoption of a systematic disruptive innovation. Mechanisms of diffusion are inherently interorganizational (Berry & Berry, 2014). That is, the probability of one institution adopting a disruptive innovation is affected by the probability that another institution adopted one. Given the research on higher education, there exist at least two plausible drivers of disruptive innovation that are demonstrative of *competition*, one of the established mechanisms of diffusion (Berry & Berry, 2014; DiMaggio & Powell, 1983): the pursuit of prestige (Brewer et al., 2001) and the pursuit of economic competition to generate revenue (Slaughter & Rhoades,

2004). I examined how these different mechanisms influenced adoption of a disruptive innovation across time and by institutional type. Studying this phenomenon required a dataset that links institutional data with data characterizing an innovation. I investigated these questions: When is MOOC adoption most likely? How does prestige-seeking behavior compared to economic competition influence the adoption of MOOCs?

1. When is MOOC adoption most likely? How does prestige-seeking behavior compared to economic competition influence the adoption of MOOCs?
2. Does partnership with a for-profit versus nonprofit provider differ by prestige-seeking behavior or economic competition? Do these partnerships change over time?
3. To what extent does a typology of institutional innovators based on prestige-seeking behavior and economic competition exist? To what extent does this typology of innovators relate to MOOC adoption? How does the adoption of innovation by institutional subgroup vary over time?

I compared two mechanisms of innovation, economic competition and prestige seeking, to evaluate the extent to which each of these mechanisms predicted the likelihood of adopting a disruptive innovation. Because the Obama administration often used economic competition to induce institutional innovation and the literature on academic capitalism posited institutional behaviors can be explained by revenue-seeking, I used variables that indicated the extent to which institutions exhibited high levels of economic competition. To assess degree of economic competitiveness, I employed five different indicators of economic competition based on the work by Slaughter and Rhoades (2004). For example, the percent of revenues from private grants and contracts was an indicator of how competitive the institution was in terms of deriving revenue

from the private sector, while increased dependence on adjuncts for teaching represented the ways institutions tried to cut costs and increase efficiencies.

These indicators are drivers of change and were included to capture different qualities of revenue-seeking or efficiency behaviors. For instance, the amount of money the institution received from private grants and contracts indicated how dependent the institution was on revenue from the private sector for research, while more distance education programs was a sign of how active the institution was in the nontraditional student market. If an institution had higher indicators of existing economic competitiveness, then I inferred that they were responsive to revenue generation and that their decision to adopt a MOOC was driven more by economic competition than by prestige seeking.

While it is often believed that market-based tactics are the most effective incentives of change, other studies of higher education have argued that an innovation that confers prestige may be more of a powerful incentive to innovate. According to the literature, increased investment in innovative behavior elevates an institution's level of prestige (Brewer et al., 2001; Christensen & Eyring, 2011). This is important because higher education institutions are prestige-maximizers (Brewer et al., 2001; Slaughter & Rhoades, 2004). Prestige is a zero-sum game because when one institution becomes more selective or attracts more research dollars, another institution loses out. Achieving higher levels of prestige is generally accomplished by increasing student quality and research capacity (Brewer et al, 2001). Institutions try to maximize their prestige because it confers more research dollars and results in higher student demand, which means institutions can fill their seats.

Brewer et al. (2001) found that institutions that were already prestigious tended to only make marginal changes to maintain their prestige because they were largely buffered from

economic pressures. In comparison, institutions with lower or no research capacity and institutions with lower selectivity were more prone to innovate in order to be able to compete on prestige. However, Walsh's (2011) findings on open educational resources (OER) and open courseware (OCW) contradicted Brewer's findings to some extent. For instance, according to Walsh, while some institutions adopted OER explicitly to generate revenue, the enduring OER and OCW programs were the ones focused on researching ways to enhance teaching and learning and improve student outcomes. Moreover, it was the most elite institutions that pioneered both OER, OCW, and MOOCs. This suggests that the most prestigious and not the institutions eager to trade up on the prestige ladder would be the most innovative. Thus, there was conflicting evidence about which institutional types are more likely to innovate.

Regardless of whether the institution is already prestigious or trying to move up the prestige ladder, prestige-seeking behavior appears to affect innovation. I take the approach that both types, at minimum, pursue it, where some might more aggressively pursue it than others. To capture the effect of prestige-seeking, I used the Carnegie Classification rankings and student admission selectivity to indicate how prestige-driven a college or university is. Presumably, if institutions have high research capacity, they are driven to pursue or maintain their degree of prestige. Because some research institutions exist that are perceived with more or less prestige than others, the Carnegie Classification on its own might be inadequate. Adding in admissions selectivity helps to draw out those differences slightly. The most prestigious institutions according to extent research on what defines prestige are then the institutions that have both high research capacity and high selectivity.

At the start of this dissertation, it was possible that both prestige-seeking and economic competition played a role in the adoption of innovation and likely they differentially explained

the patterns among different types of institutions of higher education. Yet no study to date has simultaneously tested the application of these two theories of change to examine the systematic update of disruptive innovation in higher education today.

Review of Findings

In order to first understand the relationship between indicators of prestige acquisition and economic competition and the adoption of a disruptive innovation, holding all else equal, I fit a discrete time hazard model (DTHM) to panel data from AY 2011-12 to AY 2014-15. Part of a DTHM model is the production of survival and hazard rates, which show the rates of adoption and when adoption is most likely. The advantage of using this method compared to a traditional OLS model is that it considers time invariant and time variant variables and calculates the rate of adoption only using the institutions that have never adopted a MOOC before. According to the results of this study, the rate of adoption changed over time, but the greatest likelihood of adopting MOOCs took place in 2013, two years after the first MOOC was launched. This finding implies that innovation—even if widely hyped—takes time to diffuse. However, even during the time when adoption was highest, only 3% of institutions actually adopted MOOCs in that year. While the rates of adoption refute the claim that higher education does not change, the belief that change is not rapid or penetrating the whole system has some validity.

In the main model, after controlling for time variant factors (e.g., revenues, enrollment sizes, and staffing numbers), the model suggests adopters were more prestigious than non-adopters. Both indicators of prestige (e.g., greater research activity and selectivity) were positive predictors of MOOC adoption. Adopters were also market-oriented in some ways compared to their peers; for instance, the more dependent on private grants and contracts and the more distance education programs an institution offered, the higher the odds of adopting MOOCs.

Surprisingly, very few of the other indicators of innovation already established in the literature positively predicted MOOC adoption. Only size of the institution was a strong indicator, where a one standard deviation increase in enrollment was associated with a 40% increase in the likelihood of adopting MOOCs. Finally, adopters were no more likely to rely on adjunct faculty or managers and business executives than non-adopters. They were also no more likely to offer more certificates than non-adopters. The findings also suggested that MOOC adopters were strategic in their market practices. They derived a higher portion of revenue from the private sector through private grants and contracts and expanded to nontraditional consumers through distance education programs, but they did not rely heavily on management to increase campus efficiencies or adjuncts to produce cost savings.

It should also be mentioned that while there has been a preponderance of evidence that distance education is used to generate revenue (Allen & Seaman, 2011; Christensen & Eyring, 2011; Dooley, 2000; Mettler, 2014), it may not exclusively relate economic competitiveness to the adoption of an innovation. The prior existence of distance education programs may have enabled institutions to adopt MOOCs better than institutions that do not already have robust programs. Institutions that already had distance education programs in place before adopting MOOCs may have had more technical expertise or may have developed faculty buy-in that eased the adoption of MOOCs, compared to institutions that did not have prior experience with distance education.

The second section of the results investigated the differences among indicators of prestige acquisition versus economic competition among the adopters. Because the first model only identified the factors that distinguish adopters from non-adopters, in the second model I wanted to understand how incentives varied among adopters and over time. I conducted a subgroup

analysis on just the adopters ($n = 122$). Using descriptive statistics, I examined the relationship between different indicators of institutional innovation and whether the institution partnered with a for-profit versus nonprofit MOOC provider, where partnership with a for-profit signaled a greater interest in economic competition while partnership with a nonprofit signaled greater interest in building prestige through research.

According to the results, most institutions (78%) partnered with for-profit providers, suggesting their motive was fueled primarily by economic competition. The differences in the characteristics of institutions that partnered with for-profits compared to nonprofits in AY 2011-12 and AY 2012-13 were more distinct in the last 2 years of the study, AY 2013-14 and AY 2014-15. The pioneers and early adopters that adopted MOOCs between AY 2011-12 and AY 2012-13 were highly prestigious in terms of research capacity and selectivity, and it did not matter much whether the institution partnered with a for-profit or nonprofit provider. Though the average level of prestige for new adopters became less each year for institutions that partnered with for-profit and nonprofit providers, the average level of prestige for new adopters that partnered with a for-profit provider was less compared to adopters that partnered with nonprofits for each year that went by. However, over time as the number of first-time adoptions increased, the type of institution to partner with for-profits became significantly more public, more financially constrained, and more dependent on tuition, while the first-time adopters that partnered with nonprofits tended to show fewer changes in terms of institutional capacity. What these findings suggested is that early adopters showed more characteristics of prestige-seeking behavior, while adopters in the last 2 years showed more characteristics of being financially strapped and therefore *needing* to be more economically competitive. In comparison, the institutions that partnered with the nonprofit providers were more often private institutions,

wealthier with greater cash flow and larger endowments, and were much less dependent on tuition as a source of revenue. If privates were more likely to partner with nonprofit organizations, this suggests that private colleges had greater capacity to focus on research, while the public institutions, which faced greater capacity issues, became more focused on revenue generation by partnering with for-profit providers.

Finally, the last portion of this dissertation tried to make sense of the latent grouping that emerged from examining adopters and non-adopters. The results discussed above suggested there exist unique combinations of indicators of prestige-seeking versus economic competition that affected the institutions' proclivity to adopt in innovation. That is, the predictors of institutions varied not only between adopters and non-adopters but also among adopters themselves. No adopters were characterized only by prestige-driving characteristics or economic competition characteristics. The difference between these two findings suggested that neither indicators of economic competition nor prestige fully predicted the adoption of an innovation across all adopters. A more likely scenario was that clusters of institutions were more likely to innovate, given some overlap between economic competition, prestige, and existing indicators of institutional innovation. By employing a latent class analysis (LCA), I could statistically distinguish these groups of adopters based on observable characteristics.

I used the dataset which averaged all 4 years of data (AY 2011-12 to AY 2014-15) and ran an LCA using Mplus (Muthén & Muthén, 2012). The results suggested there were five different types of innovators: Opportunists (18%), Laggards (30%), Wealth Managers (17%), Pragmatists (21%), and Accelerators (15%). Opportunists demonstrated a greater tenacity for competing in the market and looking for new places to generate revenue. Laggards were not in a position to change and had virtually no positive indicators of innovation. Wealth managers did

not compete nor were they particularly prestigious. However, they were wealthy and tended to have a heavy concentration of managers, suggesting they were concerned with building new business and increasing efficiencies on campus. Pragmatists tended to exhibit some behaviors associated with economic competition, but their tuition levels were more manageable compared to their peers. Accelerators, the final group, were extremely prestigious and strategically competitive. While most institutions in the Accelerator group did not have a high concentration of managers on their staffs to extend business practices or use adjuncts to cut costs, they did extensively use distance education and certification programs. Thus, while they were expanding their enterprise, they did it specifically by targeting student populations who were most able to pay. At the same time, they were also the institutions that were the least dependent on tuition as a percentage of their revenue.

The examination of the relationship between the types of innovators and the likelihood of adopting MOOCs revealed that institutions that exhibited both high levels of prestige seeking and economic competition were the most advanced of the innovators. On average, the Accelerators were the most likely to innovate with 38% of institutions adopting MOOCs, while the Laggards were the least likely with 0.9% of institutions adopting MOOCs. The other groups were also not very likely to innovate where adopters in each group ranged from 3% to 6% of the group. Moreover, the Accelerators were most likely to innovate first, and they innovated more often than any of the other institutional types. The Opportunists surged in AY 2013 after the headlines of 2012, while the Laggards adopted last.

Discussion

This study contributes important findings to the emergent literature on the systematic adoption of a disruptive innovation in higher education. My work augments prior research on

MOOCs, especially work by Hollands and Tirthali (2014, 2015), Allen and Seaman (2013), and DeRousie (2014), and expands existing theories on disruptive innovation in higher education. It also pioneers a new way of conceiving different groups of institutional innovators.

First, what enabled this study to advance the state of the research on disruptive innovation was the use of a much larger dataset than any of the other studies on MOOCs to date. It also explored different mechanisms by examining the types of relationships institutions pursue with providers, which no other study has done. While DeRousie's (2014) study used a DTHM to compare non-adopters to adopters to isolate which mechanisms were associated with disruptive innovation, his model suffered badly from too small a dataset and he found no significant predictors other than time. My study had more power by virtue of it taking place later, and I was able to isolate some plausible drivers of innovation that distinguished adopters from non-adopters.

Allen and Seaman (2013) reported findings from an annual survey on institutional use of and plans for MOOCs. But their findings were responses from a survey reliant on self-reporting, which introduced sampling bias that was not present in my study. Unlike in my study, in which any higher education institution that participated in or applied for any federal student financial aid programs during the years of my data collection (i.e., Pell grants and federal student loans) was required to respond to IPEDS (NCES, 2017a), in the Allen and Seaman's study responses were voluntary to the College Board study resulting in a response rate that hovered around 50%. Also, my study paired two completely different datasets in which one was required (IPEDS) and the other was machine-collected, and hence did not suffer from response bias. This meant that my findings on which institutions adopted MOOCs were more reliable than those which self-reported. For example, while Allen and Seaman found in their 2013 survey that more publics

adopted MOOCs than private nonprofits, my data showed that they were virtually tied. I found that 25 first-time adopters were private and 24 were public during AY 2013-14. However, both Allen and Seaman (2016) and Hollands and Tirthali (2015) found that institutions increasingly perceived MOOCs to be unsustainable may also be reflected in my data, where the rate of adoption declined towards the end of the data collection window.

With the current data, I was able to improve our knowledge of how disruptive innovation takes place by showing that it is not uniform in terms of timing or by type of adopters. After classifying the types of institutional innovators by the various indicators (e.g., competition, prestige, and other indicators of innovation) and examining the change over time, the findings indicated that adoption of a disruptive innovation in higher education runs counter to the ways disruptive innovation theoretically predicts. According to the original Christensen theory or disruptive innovation, a disruptive innovation emerges from an organization at the bottom of the market that then works its way up-market to ultimately displace the top competitors (Christensen Institute, 2017). This “hungry innovator” hypothesis predicts that innovation will emerge from institutions looking for a way to scale up from the lowest rungs of the existing hierarchy. However, the present analysis found that, all else being equal, these lower-rung institutions were not likely to adopt a disruptive innovation. Instead, the group of institutions most likely to adopt a disruptive innovation was the Accelerators, which are the most research-intensive and most selective of any group. Further, after analyzing their behaviors over time, this group of institutions persisted in being the most innovative, suggesting that while other types of innovators slowly entered the field, they were no match for the dominant actors of change even as time passed. In theory, the mechanism of economic competition is supposed to drive these lower-rung institutions to change the existing paradigm. However, there is no evidence that this

mechanism works under the current conditions in which a very small percentage of institutions have most of the resources and ability to absorb risk if the experiment goes wrong, while the vast majority have neither. Thus, on their own, market forces do not apparently lead to transformational change.

While my research clarified which mechanisms influence the adoption of a disruptive innovation, the policy problem was not how to incentivize 4-year institutions that have already changed to change *more*, but rather how to incentivize change in the institutions least likely to innovate in the first place (Baum et al., 2013; Brewer & Tierney, 2010; Christensen & Eyring, 2011). What do these findings say about the types of institutions that are less likely to innovate? Overshadowed by the elite institutions, the “underdogs” of innovation have a decidedly different profile than the institutions that led the early years of MOOC adoption. Until this study, limited empirical and conceptual work on what characterizes innovators and non-innovators has maligned the reputation of higher education generally and has left uncovered important implications that have impeded useful policy and regulatory reforms. While my results do not confirm why certain types of institutions are unlikely to innovate, they are at least suggestive of the barriers to disruptive innovation. If there is the impression that disruptive innovation is not taking place at a fast enough rate, my results suggest there are three potential challenges that might lead to a slow uptake: lack of prestige-seeking behavior, lack of strategic competitiveness, and lack of financial capacity.

The first potential issue that limits innovation is that non-prestigious institutions may be hindered by their non-prestigious status or lack of prestige-seeking behavior. In the first section, the major distinction between the adopters and non-adopters was prestige-seeking behavior. Then, in the second section, the results indicated that adopters in AY 2011-12 were considerably

more prestigious than the adopters that partnered with for-profit providers in AY 2014-15. Finally, in the third section, where the Accelerators were fueled by research and selective admissions, the Wealth Managers, Pragmatists, and Laggards had virtually no evidence of these behaviors. Only the Opportunists included some prestigious institutions, and it was this group, after the Accelerators, which was the most likely to offer MOOCs. These findings suggest that prestige-seeking behavior affects not just the likelihood of adoption, but also the timing. Those institutions with the lower research intensity and less selective admissions are not likely to innovate early on or at all.

Second, not being competitive in specific domains may impede the adoption of a disruptive innovation. The provision of distance education (e.g., online education) was the single-most consistent predictor of innovation across all three sections. In this study, the number of distance education programs offered by an institution was used as an indicator of how competitive the institution was in the nontraditional student market. The results empirically showed that the more competitive the institution was in terms of distance education programs offered, the more likely the institution was to offer MOOCs. According to the results of the LCA, 75% of Accelerators and 66% of Opportunists offered an above average number of distance education programs, while only 34% of Laggards offered an above average number of distance education programs. While my framework employed distance education as an indicator of the institution's level of competitiveness in a market of nontraditional consumers of education, merely having experience with it may also prove to be a key antecedent of engaging disruptive innovation. Perhaps already having distance education reduced the complexities of adopting MOOCs for the first time or mitigated faculty resistance to adopting the new innovation.

In addition to not being competitive in the distance education market, not being competitive in the certification programs may also be symptomatic of limited institutional capacity to engage disruptive innovation. While the presence of certification programs did not statistically predict the difference between adopters and non-adopters, it did seem to be an important distinguisher of the LCA results that also included the full sample. Similar to the distance education programs, the institutions that had more certificate programs were more likely to be innovators and earlier innovators at that. For example, both the Accelerators and the Opportunists included a large proportion of institutions that offered more than the average in terms of certification programs (e.g., 82% and 74%, respectively), while the Laggards and Wealth Managers included many fewer highly competitive institutions in terms of certification programs.

Third, and finally, the lack of institutional capacity to innovate (e.g., small endowments, low cash flow, and high dependence on tuition) may also present barriers to deploying a disruptive innovation. Dominic Brewer and William Tierney (2010) argued that the for-profit and non-elite are the most likely to innovate since they have neither a large endowment nor prestigious reputations that guarantee many applicants willing to pay the full price. Without those safeguards, these institutions presumably are the hungriest to change. While I cannot comment on how the resources of for-profits compared to the Laggards in this study, I can affirm that the nonprofit non-elite private group of institutions, which made up the Laggards, was the *least* likely to innovate when presented with a new opportunity. Moreover, it was this group that suffered the most in terms of available financial capacity to adopt MOOCs. New technologies are expensive and require experimentation (Brewer et al., 2001; Brewer & Tierney, 2010). For example, Hollands and Tirthali (2014) estimated that the first MOOC launch could cost anywhere between \$200,000 and \$325,000 (p. 144). Therefore, the institutions that have smaller

endowments and low cash flow (slack resources) are probably financially constrained and unable to take the risk associated with innovating. The likelihood of innovating is depressed even further if the institution is extremely tuition-dependent. Institutions that are tuition-dependent and lack large endowments, usually small private nonprofit colleges, are unable to compete with colleges that are less tuition-dependent (e.g., public institutions) or with colleges that have bigger endowments that allow them to provide students with more generous financial aid packages (Rivard, 2013d).

Policy Implications

The theory of disruptive innovation posits that higher education will evolve when competition is introduced from new entrants in the lower tiers (Christensen & Eyring, 2011). It may be for this reason that the Obama administration and policymakers embraced innovation from nontraditional sources (e.g., bootcamps, coding academies, and coalitions of for-profit and nonprofit organizations). Yet, the results in this study suggested that the dominant, traditional institutions still hold a tight grasp on innovation in higher education, where institutions that are associated with the greatest status are unquestionably not only the most innovative but also the earlier innovators. Despite efforts to increase competition from lower-tier institutions, there appears to be only hints of activity from those institutions. Why is that?

According to Brewer and Tierney (2010), innovation occurs when the incentives to innovate are strong and, conversely, less likely when the incentives are weak. This means that policymakers must put into practice the right incentives in order to engender the transformational change they are seeking. Since only 3.5% of institutions were likely to adopt MOOCs at the height of adoption and only 8% of the sample ever adopted a MOOC, the type of incentive and support necessary to induce change seemed to be missing. The results of the LCA indicated that

a particular group of institutions was incentivized to innovate far above the others. On average, 35% of the Accelerators adopted a MOOC, while the remaining groups reported low single-digit adoption rates for MOOCs. What distinguished this group from the others was the presence of a combination of prestige-seeking and strategic economic competition, suggesting that this is the combination of incentives institutions need to adopt a disruptive innovation. Without these drivers, institutions are not likely to change.

Knowing that a combination of incentives appears to drive higher rates of disruptive innovation, how do policy and politics better incentivize innovation that improves affordability and access to high quality education? Federal and state policymakers may encourage better innovation by tailoring their policies to specific groups of institutions rather than employ a generic policy instrument. Treating institutions as monolithic innovators (or non-innovators) overlooks that different institutions face different constraints. For example, by incentivizing disruptive innovation through financial instruments without simultaneously taking into account the fact that different types of innovators face different capacity constraints (e.g., slack resources), the groups most in need of innovation (e.g., Laggards, Opportunists, and Pragmatists) will probably remain immune to innovation. This is because the institutions that already have the capacity to innovate are rewarded for activities they are already successful at, while institutions that may face greater challenges because of capacity issues are stymied right from the beginning. Research on performance funding has found that too little attention to the different capacities of institutions meant that low-capacity institutions could not respond nearly as well as high-capacity institutions to the performance funding initiatives (Dougherty et al., 2016). To avoid this issue, a better approach may be to provide institutions with more direct funding to experiment with innovation without penalizing them if the experiment does not immediately produce positive

results. Case in point, when San Jose University experimented with the for-profit provider Udacity to use MOOCs to offer remedial and introductory courses, the first-year outcomes were dismal and the experiment was abruptly halted (Coyle, 2015). Because the stakes are so high in terms of accountability, institutions that need to demonstrate high performance or risk losing valuable funding are not likely to try new provisions of education if they are penalized for not making gains early on. Yet, the research on which institutions adopted MOOCs, OER, and OCW has suggested that room to experiment is key (Hollands & Tirthali, 2014, 2015; Walsh, 2011).

Ironically, the institutions that need to innovate the most (e.g., institutions that have high-tuition dependence or need to adjust their offerings to help students better meet current job requirements) are the most likely to be penalized for poor performance. Institutions, like San Jose State University, which belong to the “Pragmatists” LCA subgroup serve the majority of nontraditional and disadvantaged students. These students also have the hardest time succeeding with online education and alternative types of education, while the majority of students who thrive are well-educated self-learners (Waks, 2016; Xu & Jaggars, 2011). Therefore, creating effective, alternative models for these types of students will require greater investment in institutional infrastructure and provisions for experimentation.

As described above, the creation of a new group of statistically distinguishable institutional innovators, grouped by their observable characteristics, ultimately adds an important stepping block to understanding higher education adoption of a disruptive innovation. To date, there are no classification schemas that categorize innovators, which has limited research on the facilitators and obstacles to disruptive innovation. For example, Barron’s Admissions Index ranks schools according to a proprietary set of guidelines, and this assessment is usually only used to measure prestige or “college competitiveness” (NCES, 2009). The Carnegie

Classification is another system that categorizes institutions according to their research capacity (Carnegie Classification of Institutions of Higher Education, 2017). Moreover, there are various models that categorize institutions according to their teaching versus research capacity (Brewer et al., 2001; Marginson, 2006). Yet, to my knowledge, no empirically derived group other than mine exists. The creation of these groups provides policymakers with discrete institutional groupings separated by observable characteristics and behaviors towards markets, prestige, and innovation. The creation of such groups provides areas for future research that target those groups specifically, and it provides policymakers a way to tailor policies and direct resources to induce innovation effectively and avoid some of the mishaps that take place when policy is not designed for specific contexts.

Nevertheless, if state and federal funding levels are to remain at current levels and the neoliberal model of turning to private sector partnerships to increase efficiency and decrease costs persists, then additional regulatory safeguards will need to be put in place in order to prevent student exploitation by companies more interested in turning a profit than providing high-quality and effective instruction (Deming, Goldin, & Katz, 2011; Mettler, 2014). This precaution is in light of the recent for-profit college scandals that have emerged. In the 1990s, the for-profits rose to meet demand not filled by the traditional 4-year institutions. These institutions were heralded for their innovativeness since they were among the first to widely adopt online education and, as a result, were able to grow their enrollments exponentially (Deming et al., 2011). For-profit colleges were able to grow quickly because of the 90/10 rule that allows institutions to collect up to 90% of their operating revenue from federal student aid money. Over the years, however, it has surfaced that these colleges participated in unscrupulous business practices. According to the results of a 2011 study conducted by David Deming, Claudia Goldin

and Lawrence Katz, students at for-profit colleges ended up with higher unemployment and “idleness rates” and lower earnings after 6 years relative to students at traditional colleges; they also had much higher debt loads and defaulted on their loans at much greater rates than students at traditional colleges and universities. Now, because of the Federal Gainful Employment Act of 2015, the U.S. Department of Education plans to close more than 800 vocational programs that have failed to show that their graduates could find meaningful employment allowing them to pay back their student loans (DeRuy, 2017). With careful planning, perhaps these types of closures can be avoided. Regardless, careful attention needs to be paid to this matter if partnerships between institutions of higher education and for-profit providers become the new norm for disruptive innovation (e.g., Coursera and Canvas).

Limitations of the Present Study and Areas for Future Research

While I argue that the results of this study are significant, several limitations must be discussed. First, the study would have benefitted from more years of MOOC data to draw out the differences across institutional groups with stronger statistical power and more precise estimates. The analysis in Section 2 was particularly affected by a small sample. Because there were only 122 adopters, I could not employ more rigorous statistical tests. While the findings were substantively interesting, their statistical significance should be interpreted with caution. Knowing whether the differences are statistically different while controlling for other variables would have improved the rigor of these findings. However, because these data and the investigations into using online education as disruptive innovation in higher education are a new phenomenon, more data will be available in the years to come.

Second, while my dataset is the most comprehensive to date on the institutional adoption of MOOCs, more than 40% of four-year public and non-profit private institutions were

eliminated because of missing data (see Appendix D). As shown in Table D2 of Appendix D, the findings in this study are not generalizable to the entire population of four-year public and private colleges and universities in the US. Across each of my variables of interest, there were significant differences between the institutions that remained in the study compared to those deleted. The source of the greatest attrition of data was from the Religious/Other group, which comprised faith-based colleges, specialty institutions, and institutions that also award associate's degrees. Deleted institutions, on average, were less selective, more reliant on adjuncts and managers, more public, and more financially constrained than institutions that remained in the study. My findings are thus not generalizable to all institutions, but rather to institutions that are not faith-based, tribal, or specialty schools and which have more selective admissions criteria, and more robust enrollments and financial resources. The institutions that were deleted, however, do have characteristics that are very similar to the laggards, thus it is likely that the parameters and standard errors for the laggard group identified in the LCA are especially biased and could be improved upon with better data.

Finally, these findings also reported on the diffusion of only one disruptive innovation, MOOCs. MOOCs are expensive innovations to produce and it may be that the patterns I identified in this study are only applicable to expensive innovations and are dependent on the institutions having high levels of wealth and existing infrastructure to launch them. There is a range of innovations and potentially even disruptive innovations. Lower up front capital investment may result in the adoption patterns of different innovations. As such, findings about capacity and size may show up more when look at one type of innovation versus another one. For example, there may also be other innovations that are also utilized to save time and cut costs but which do not require the same level of resources that MOOCs do to implement. Thomas

Bailey, Shanna Smith Jaggars, and Davis Jenkins (2015) proposed a Guided Pathways program to replace the student self-service or “cafeteria” style of course selection with a highly structured plan that guides students through program completion faster and more economically. Guided Pathways may be an example of a new disruptor to the educational status quo but which does not require the same amount of resources as MOOCs to implement. Also, previous use of distance learning could be very specific to MOOCs. Since MOOCs are a type of online education, it may not be so surprising that institutions already with distance education in place are more likely to adopt MOOCs. However, if we continue to use this Guided Pathways model as an example, the prior existence of distance education may not be highly predictive of adopting Guided Pathways. Perhaps experience with other advising or counseling innovations may be more predictive of whether a college adopts Guided Pathways or not. It may be that prior experience with an innovation that is similar to the new one being adopted correlates with the adoption of similar types of innovations. Testing the extent to which the models proposed in this study fit the diffusion of that innovation would be one very important next step to testing the generalizability of the model findings to other innovations.

Additionally, the findings in this dissertation were only proxy measures of prestige seeking and economic competition. From these proxies, I made claims about what mechanisms effectively incentivized and obstructed the systematic adoption of a disruptive innovation. The findings would therefore be improved considerably with a qualitative study that investigates the obstacles to innovation according to the subgroups that emerged in the LCA.

Because this is an area of budding research, many studies can and should be conducted to improve our understanding of what incentivizes disruptive innovation in traditional higher education. Additional research might use the framework presented in this dissertation to examine

the rise of other disruptive innovations that have emerged in recent years. These include short-term certification programs (Udacity, 2017), whole years of college work that are being offered through a MOOC provider such as the Global Freshman academy (edX, 2017), and competency-based education programs (Educause, 2017), or perhaps the push for faster Bachelor's degrees and Master's degrees via fully online programs (MOOCs University, 2017; Straumsheim, 2016). The current model could be applied to their adoption to test the endurance and validity of the findings.

This dataset can answer many more questions related to the adoption and diffusion of MOOCs (i.e., penetration into different markets through analysis of courses and departments) and can even be used for a comparative study of U.S. versus international producers and providers to assess U.S. hegemony. But there remain several other areas to which these data can be applied. For instance, another interesting application would be to examine the extent to which disruptive innovation in public higher education is tied to decentralized or centralized state higher education systems.

Finally, testing other mechanisms of diffusion, including learning, coercion, and imitation, normative pressures, or regional diffusion (Berry & Berry, 2014), would benefit research on disruptive innovation in higher education. For example, many researchers have suggested that higher education institutions tend to *imitate* more successful colleges and universities (Christensen & Eyring, 2011). According to institutional theory, imitation often takes place during times of uncertainty or when technologies are not known (DiMaggio & Powell, 1983). As was described in detail in the literature review, at the point that MOOCs entered the higher education landscape, the political and economic environment was especially uncertain and pressures abounded to lower costs and increase access, but also—from the institutional

perspective—maintain revenue. Then, MOOCs were also a technical solution that were not well understood, especially in terms of how they would generate revenue or solve the access issue. Thus, given these conditions, it would be most informative to conduct a qualitative study on whether the diffusion of MOOCs, especially under conditions of uncertainty, was undertaken as an effort to copy their peers to achieve stability and legitimacy during an otherwise rocky time—or whether competition for prestige and market share were bigger influences of change.

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Appendix A: Discrete Time Hazard Model Code

```
1 // Lara Pheatt
2 // Started 10-01-16 (Original File = hazard_model.do)
3 // Last Updated: 3-28-17
4 // hazard model
5 // use: Analysis/merge_hazmod_clean.dta
6 // save: Analysis/hazmod_institution_period_clean.dta", replace
7
8
9 /*
10 1. reduce MOOCs data to initial adoption year
11 2. merge with IPEDS data
12 3. create life table
13 */
14
15 // NOTES: Begin file for hazard model (gen first event).
16 // Subsequent events are eliminated in this file.
17
18 set more off
19 clear all
20
21 use Analysis/merge_paneldta_clean.dta, clear // balanced dataset
22 clear
23
24 // for descriptives at top of paper
25 sum carn1 carn2 carn3 carn4 selective cntrctr2 pmanage padjunct
26 ptotalde totcert public z_cashflow z_endow z_enroll tuitr2
27
28 ** Final Measures (Minimizes issues of multicollinearity)
29 ** NOTE: ENDOWMENT, DISTANCE cannot be included
30 ** Removed institutional support since I cannot clearly
31 ** distinguish what it includes in finance survey
32 ** removed hiexp and acasup too because these are not tied to
33 the theory
34
35 xtset
36
37 reg moocinst carn1 carn2 carn4 selective cntrctr2 pmanage
38 padjunct ptotalde totcert ///
39 public z_cashflow z_endow tuitr2 z_enroll
40
41 estat vif // no multicollinearity issues
42
43 ** LIFE TABLE
44
45 ** Gen institution level data set
46 //for institution-level data set (for basic survival and
47 hazard model, see page 327 & 353 in Singer & Willett, 2003.
48
49 preserve
```

```

45      sum carn1 carn2 carn3 carn4 selective cntctr2 pmanage
      padjunct ptotalde totcert public z_cashflow z_endow tuitr2 z_enroll

46
47      collapse (max) moocyear moocinst carn1 carn2 carn3
      carn4 public ///
48      (mean) selective cntctr2 pmanage padjunct ptotalde
      totcert z_cashflow z_endow tuitr2 z_enroll, by(unitid)
49
50      gen time = moocyear - 2010
51      replace time = 4 if time==.
52      label var time "time of event occurrence. 2011 is
      the beginning of time"
53
54      gen censor = (time ==4 & moocyear ==.)
55      label var censor "whether institution is censored
      or not"
56
57      gen id = _n
58
59      sort id
60
61      export excel id time censor moocyear carn1 carn2 carn3
      carn4 selective cntctr2 pmanage padjunct ///
62      ptotalde totcert public z_cashflow z_endow tuitr2
      z_enroll ///
63      using "Analysis/hazmod_institution_level_clean2.xlsx",
      firstrow(variables) replace
64
65      outfile id time censor ///
66      using "Analysis/hazmod_institution_level_clean2.csv",
      comma replace
67      ** Note, you had to manually add in a title line for
      spss to read (id, time, censor)
68      ** in field called
      "Analysis/hazmod_institution_level_clean2.csv"
69      ** You will need to do this each time until you can
      figure out
70      ** how to add a line for variable names
71
72
73      save "Analysis/hazmod_institution_level_clean2.dta",
      replace
74
75      restore
76
77      ** Gen Life Table (p. 327 Singer & Willett, 2003)
78      use "Analysis/hazmod_institution_level_clean2.dta". clear

```

```

78 use "Analysis/merge_paneldta_clean.dta", clear
79 keep id time censor
80 gen event = ~ censor
81 ltable t event, noadjust // For survival rate
82
83 ltable t event, hazard noadjust // For hazard rate
84
85 ** Hazard Plot
86 stset t, failure(event)
87 sts gen h=h
88 graph twoway scatter h t, msymbol(i) connect(l) ylabel(0(
.01).04) xlabel(0(1)4) sort
89
90 ** Survival Plot
91 ltable t event, noadjust notab graph noconf xlabel(0(1)4)
ylabel(0(.1)1) yline(.5) xline(7.6)
92
93 ltable t event, noadjust survival hazard
94
95 ** DISCRETE TIME HAZARD MODEL
96
97 ** Gen institution period data set for DTHM Full Model (p.
98
99 use "Analysis/merge_paneldta_clean.dta", clear
100
101 ** create group id
102 egen id = group(unitid)
103
104 ** create event
105 bysort unitid(moocyear): gen event = 1 if moocyear !=. //
Creates event
106
107 ** Generate institution-period data set (see p 352 & 380 in
S&W, 2003)
108 bysort unitid: egen moocyear2 =min(moocyear)
109 drop if moocyear > moocyear2
110 drop moocyear2
111 replace event = 0 if event ==.
112
113 gen period = .
114 replace period =1 if year ==2011
115 replace period =2 if year ==2012
116 replace period =3 if year ==2013
117 replace period =4 if year ==2014
118
119 gen d1 =1 if period == 1
120 replace d1 =0 if period !=1
121
122 gen d2 =1 if period ==2
123 replace d2 =0 if period !=2

```

```

123         replace d2 =0 if period !=2
124
125     gen d3 =1 if period == 3
126     replace d3 =0 if period !=3
127
128     gen d4 =1 if period == 4
129     replace d4 =0 if period !=4
130
131     tab period event, row
132
133     /*foreach x of varlist degrant2 public fouryear prestige
instsize {
134         bysort unitid (year): carryforward `x', replace
135     }*/
136
137     sort unitid period
138
139     outfile id period event d1 d2 d3 d4 carn1 carn2 carn4 ///
140     selective cntctr2 pmanage padjunct ptotalde totcert ///
141     public z_cashflow z_endow tuitr2 z_enroll ///
142     using "Analysis/hazmod_institution_period_clean2.csv",
comma replace
143
144     export excel id period event d1 d2 d3 d4 ///
145     carn1 carn2 carn3 carn4 selective cntctr2 pmanage padjunct
///
146     ptotalde totcert public z_cashflow z_endow tuitr2 z_enroll
using "Analysis/hazmod_institution_period_clean2.xlsx", firstrow (
variables) nolabel replace
147
148     // See
http://stats.idre.ucla.edu/stata/examples/alda/chapter11/ for
examples on DTHM
149
150     save "Analysis/hazmod_institution_period_clean.dta", replace
151     // Code for Survival Model
152
153     ltable year event, noadjust survival hazard
154
155     ** Model A
156     logistic event d1 d2 d3 d4, nocons // "Logistic" Displays
Odds-Ratios
157     logit event d1 d2 d3 d4, nocons // "Logit" displays log
odds coefficients
158     quietly logit event d1 d2 d3 d4
159     fitstat
160
161     logit event d1 d2 d3 d4, nocons
162     outreg2 using Results/hazmod/hazmodmodelA.xls, replace
163     attitle(Model A)

```



```

ctitle(Model A)
163
164     ** Model B
165     logistic event d1 d2 d3 d4 carn1 carn2 carn4 selective,
nocons
166     logit event d1 d2 d3 d4 carn1 carn2 carn4 selective, nocons
167     quietly logit event d1 d2 d3 d4 carn1 carn2 carn4 selective
168     fitstat
169
170     logistic event d1 d2 d3 d4 carn1 carn2 carn4 selective, nocons
171     outreg2 using Results/hazmod/hazmodelB.xls, replace ctitle(
Model B)
172
173     ** Model C
174     logistic event d1 d2 d3 d4 cntrctr2 pmanage padjunct
ptotalde totcert, nocons
175     logit event d1 d2 d3 d4 cntrctr2 pmanage padjunct ptotalde
totcert, nocons
176     quietly logit event d1 d2 d3 d4 cntrctr2 pmanage padjunct
ptotalde totcert
177     fitstat
178
179     logistic event d1 d2 d3 d4 cntrctr2 pmanage padjunct ptotalde
totcert, nocons
180     outreg2 using Results/hazmod/hazmodelC.xls, replace ctitle(
Model C)
181
182     ** Model D
183     logistic event d1 d2 d3 d4 ///
184     carn1 carn2 carn4 selective ///
185     cntrctr2 pmanage padjunct ptotalde totcert ///
186     public z_cashflow z_endow tuitr2 z_enroll, nocons
187     logit event d1 d2 d3 d4 ///
188     carn1 carn2 carn4 selective ///
189     cntrctr2 pmanage padjunct ptotalde totcert ///
190     public z_cashflow z_endow tuitr2 z_enroll, nocons
191     quietly logit event d1 d2 d3 d4 ///
192     carn1 carn2 carn4 selective ///
193     cntrctr2 pmanage padjunct ptotalde totcert ///
194     public z_cashflow z_endow tuitr2 z_enroll
195     fitstat
196
197     logit event d1 d2 d3 d4 ///
198     carn1 carn2 carn4 selective ///
199     cntrctr2 pmanage padjunct ptotalde totcert ///
200     public z_cashflow z_endow tuitr2 z_enroll, nocons
201     outreg2 using Results/hazmod/hazmodelD.xls, replace
ctitle(Model D)
202

```

Appendix B: Subgroup Analysis of Mechanisms by Provider Code

```
1 // Lara Pheatt
2 // September 12, 2016: March 2, 2017
3 // use: derived/moocs_clean.dta
4 //       derived/ipeds_merged.dta
5 // Saved tables: Table3_producerXnonprodXsector.xls,
6
7 clear all
8 set more off
9
10 // use panel data for this analysis over time
11
12     use Analysis/merge_subgroupv2.dta, clear
13     outfile using Analysis/merge_subgroupv2.txt, comma replace
14
15     // drop if provider == "" because it's a balanced dataset some
16     // schools that haven't adopted
17     // MOOCs yet will have a missing profprovdr
18
19     ** Note the variables used in the Haz Mod were: carn2 carn3
20     carn4
21     ** selective tuitr2 cntctr2 pmanage padjunct ptotalde totcert
22     ** public hicash hiendow gradrate z_enroll.
23
24 // determine number of providers
25     tab year rprovider2
26
27 // percentage for profit increases over-time
28     tab profprovdr year, chi2
29
30 // Summary of relationship between providers and adopters for all
31 // years averaged (2011-2014)
32 // (Table 2.1)
33     preserve
34     drop if profprovdr == .
35     collapse (sum) count (mean) mcarn1=carn1 mcarn2=carn2
36     mcarn3 = carn3 mcarn4 = carn4 mselect = selective ///
37     mcontract = cntctr2 mpmanage = pmanage mpadjunct =
38     padjunct mptotalde = ptotalde mtotcert= totcert ///
39     mpublic = public mcash = cashflow mendow =endow mtuitr2=
40     tuitr2 menroll=enroll ///
41     (sd)sdcarn1=carn1 sdcarn2=carn2 sdcarn3=carn3 sdcarn4=carn4
42     sdselect= selective sdcontract = cntctr2 ///
43     sdpmmanage = pmanage sdpadjunct=padjunct sdptotalde=ptotalde
44     sdtotcert=totcert ///
45     sdpublic=public sdcash=cashflow sdendow=endow sdtuit=tuitr2
46     sdenroll=enroll ///
47     , by(profprovdr)
48
49     order count mcarn1 sdcarn1 mcarn2 sdcarn2 mcarn3 sdcarn3
```

```

mcar4 sdcar4 mselect sdselect ///
41      mcontract sdcontract mpmanage sdpmanage mpadjunct
sdpadjunct mptotalde sdptotalde ///
42      mtotcert sdtotcert mpublic sdpublic mcash sdcash mendow
sdendow mtuit sdtuit ///
43      menroll sdenroll
44
45      xpose, clear varname format (%6.2f)
46
47      order _varname
48      export excel using Results/Practices/adoptersXproviders_avg
.xlsx, firstrow(varlabels) replace
49
50      restore
51
52  // Statistical Tests for Table 2.1
53      tab carnegie profprovdr, col chi
54      ttest selective, by(profprovdr)
55      ttest cntrctr2, by(profprovdr)
56      ttest pmanage, by(profprovdr)
57      ttest padjunct, by(profprovdr)
58      ttest ptotalde, by(profprovdr)
59      ttest totcert, by(profprovdr)
60      tab public profprovdr, col chi
61      ttest cashflow, by(profprovdr)
62      ttest endow, by(profprovdr)
63      ttest tuitr2, by(profprovdr)
64      ttest enroll, by(profprovdr)
65
66  // Summary of relationship over time – Year by Year Avg (2.2)
67
68  preserve
69
70      drop if profprovdr == .
71      collapse (sum) count (mean) mcar1=car1 mcar2=car2
mcar3 = car3 mcar4 = car4 mselect = selective ///
72      mcontract = cntrctr2 mpmanage = pmanage mpadjunct =
padjunct mptotalde = ptotalde mtotcert= totcert ///
73      mpublic = public mcash = cashflow mendow =endow mtuitr2=
tuitr2 menroll= enroll ///
74      (sd)sdcar1=car1 sdcar2=car2 sdcar3=car3 sdcar4=car4
sdselect= selective sdcontract = cntrctr2 ///
75      sdpmanage = pmanage sdpadjunct=padjunct sdptotalde=ptotalde
sdtotcert=totcert ///
76      sdpublic=public sdcash=cashflow sdendow=endow sdtuit=tuitr2
sdenroll=enroll, by(year)
77
78      order count mcar1 sdcar1 mcar2 sdcar2 mcar3 sdcar3
mcar4 sdcar4 mselect sdselect ///

```

```

79      mcontract sdcontract mpmanage sdpmanage mpadjunct
sdpadjunct mptotalde sdptotalde ///
80      mtotcert sdtotcert mpublic sdpublic mcash sdcash mindow
sdindow mtuit sdtuit ///
81      menroll sdenroll
82
83      xpose, clear varname format (%6.2f)
84
85      order _varname
86      export excel using Results/Practices/adoptersXyear.xlsx,
firstrow(varlabels) replace
87
88      restore
89
90
91  // Summary of relationship between providers and adopters by year
(Table 2.3)
92
93      preserve
94
95      drop if profprovdr == .
96      collapse (sum) count (mean) mcarn1=carn1 mcarn2=carn2
mcarn3 = carn3 mcarn4 = carn4 mselect = selective ///
97      mcontract = cntrctr2 mpmanage = pmanage mpadjunct =
padjunct mptotalde = ptotalde mtotcert= totcert ///
98      mpublic = public mcash = cashflow mindow =indow mtuitr2=
tuitr2 menroll= enroll ///
99      (sd)sdcarn1=carn1 sdcarn2=carn2 sdcarn3=carn3 sdcarn4=carn4
sdselect= selective sdcontract = cntrctr2 ///
100     sdpmanage = pmanage sdpadjunct=padjunct sdptotalde=ptotalde
sdtotcert=totcert ///
101     sdpublic=public sdcash=cashflow sdindow=endow sdtuit=tuitr2
sdenroll=enroll, by(profprovdr year)
102
103     order count mcarn1 sdcarn1 mcarn2 sdcarn2 mcarn3 sdcarn3
mcarn4 sdcarn4 mselect sdselect ///
104     mcontract sdcontract mpmanage sdpmanage mpadjunct
sdpadjunct mptotalde sdptotalde ///
105     mtotcert sdtotcert mpublic sdpublic mcash sdcash mindow
sdindow mtuit sdtuit ///
106     menroll sdenroll
107
108     xpose, clear varname format (%6.2f)
109
110     order _varname
111     export excel using Results/Practices/
adoptersXprovidersXyear.xlsx, firstrow(varlabels) replace
112
113     restore

```

```

113 restore
114
115 // Statistical Tests for Table 2.3
116
117 preserve
118     keep if year == 2011
119
120     tab carnegie profprovdr, row chi
121     ttest selective, by(profprovdr)
122     ttest cntrctr2, by(profprovdr)
123     ttest pmanage, by(profprovdr)
124     ttest padjunct, by(profprovdr)
125     ttest ptotalde, by(profprovdr)
126     ttest totcert, by(profprovdr)
127     tab public profprovdr, col chi
128     ttest cashflow, by(profprovdr)
129     ttest endow, by(profprovdr)
130     ttest tuitr2, by(profprovdr)
131     ttest enroll, by(profprovdr)
132
133 restore
134
135 preserve
136     keep if year == 2012
137
138     tab carnegie profprovdr, row chi
139     ttest selective, by(profprovdr)
140     ttest cntrctr2, by(profprovdr)
141     ttest pmanage, by(profprovdr)
142     ttest padjunct, by(profprovdr)
143     ttest ptotalde, by(profprovdr)
144     ttest totcert, by(profprovdr)
145     tab public profprovdr, col chi
146     ttest cashflow, by(profprovdr)
147     ttest endow, by(profprovdr)
148     ttest tuitr2, by(profprovdr)
149     ttest enroll, by(profprovdr)
150
151 restore
152
153
154 preserve
155     keep if year == 2013
156
157     tab carnegie profprovdr, row chi
158     ttest selective, by(profprovdr)
159     ttest cntrctr2, by(profprovdr)
160     ttest pmanage, by(profprovdr)
161     ttest padjunct, by(profprovdr)
162     ttest ptotalde, by(profprovdr)

```

```
162         ttest ptotalde, by(profprovdr)
163         ttest totcert, by(profprovdr)
164         tab public profprovdr, col chi
165         ttest cashflow, by(profprovdr)
166         ttest endow, by(profprovdr)
167         ttest tuitr2, by(profprovdr)
168         ttest enroll, by(profprovdr)
169
170     restore
171
172     preserve
173         keep if year == 2014
174
175         tab carnegie profprovdr, row chi
176         ttest selective, by(profprovdr)
177         ttest cntrctr2, by(profprovdr)
178         ttest pmanage, by(profprovdr)
179         ttest padjunct, by(profprovdr)
180         ttest ptotalde, by(profprovdr)
181         ttest totcert, by(profprovdr)
182         tab public profprovdr, col chi
183         ttest cashflow, by(profprovdr)
184         ttest endow, by(profprovdr)
185         ttest tuitr2, by(profprovdr)
186         ttest enroll, by(profprovdr)
187
188     restore
189
```

Appendix C: Mplus Code for LCA Analysis

```
Title:
University Innovation Study, 2010-2014 Data ;

Data:
File = mplus_lca_clean1h.csv;

Variable:
NAMES = ID
      hirsrch hisel hicntrt himnge hiadj hide hicert
      public hicash hiendow hitui hienr moocinst ;

MISSING = ALL (99999);

IDVARIABLE = ID;

USEVARIABLES = hirsrch hisel hicntrt himnge hiadj hide
               hicert public hicash hiendow hitui hienr ;

CATEGORICAL = hirsrch hisel hicntrt himnge hiadj hide
               hicert public hicash hiendow hitui hienr ;

CLASSES = c(5); ! Prestige versus Market

! AUXILIARY = (R3STEP) moocinst
AUXILIARY = (DCAT) moocinst;
!Command syntax for Step 3;

ANALYSIS:
Type=mixture;
Starts = 2500 100
LRTSTARTS = 0 0 100 20

Plot:
TYPE = plot3;
SERIES = hirsrch hisel hicntrt himnge hiadj hide
         hicert public hicash hiendow hitui hienr (*);

OUTPUT:
TECH11 TECH14

Savedata:
SAVE = CPROBABILITIES ;
FILE = cprobs-001.dat ;
FORMAT = free ;
ESTIMATES = mixest-001.dat ;
```

Appendix D: Missing Data Analysis

Table D1. Missing Data for Starting Sample Pre-listwise Deletion (n=2509)

	Missing	Total Observations (Panel Data)	Percent Missing
Carnegie Classification	0	9,773	0
Selectivity	3,141	9,773	32.14
Private grants and contracts as % of revenue	662	9,773	6.77
Management as % of total staff	257	9,773	2.63
Adjuncts as % of total instructional staff	641	9,773	6.56
Distance education programs	180	9,773	1.84
Certification programs	180	9,773	1.84
Public	0	9,773	0
Cash flow	662	9,773	6.77
End of year endowment	662	9,773	6.77
Net tuition as % of total revenue	662	9,773	6.77
Enrollment	292	9,773	2.99

Table D2. Comparing Determinants by Missing (deleted) Cases

	Not-Deleted (n=1,470)	Deleted (1,039)
Prestige		
Carnegie (%) ***		
Research	0.18	0.23
Masters	0.38	0.10
Bachelors	0.34	0.18
Religious/Other	0.10	0.70
Selectivity ***	0.36 (0.02)	0.27 (0.01)
Private grants/contracts (% rev) ***	0.01 (0.00)	0.02 (0.00)
Management as % staff ***	0.11 (0.00)	0.14 (0.00)
Adjuncts as % of staff ***	0.16 (0.00)	0.26 (0.00)
Distance education programs***	2.91 (0.10)	1.92 (0.12)
Certification programs **	3.33 (0.12)	2.56 (0.15)
Public (%) ***	0.29	0.54
Cash flow ***	2.78e+07 (2351138)	4184446 (440346)
End of year endowment ***	2.75e+08 (1.87e+07)	3.45e+07 (2332177)
Net tuition as % of revenue ***	0.56 (0.00)	0.51 (0.01)
Enrollment ***	6909.78 (120.25)	2374.29 (100.26)

Standard errors are in parentheses

p<.001 ***, p<.01 **, p<.05 *